MODERATING EFFECTS OF OCCUPATIONAL HEALTH EXPOSURES AND MEDICATION ADHERENCE: MODELS FOR IMPROVED ADHERENCE

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Submitted to the Graduate Faculty of

Graduate School of Public Health in partial fulfillment

of the requirements for the degree of

Doctor of Public Health

University of Pittsburgh

2015

UNIVERSITY OF PITTSBURGH

GRADUATE SCHOOL OF PUBLIC HEALTH

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September 4, 2015

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ABSTRACT

Medication adherence is of great public health importance as medication non-adherence greatly affects chronic disease burden and total healthcare spending. This prospective research study hypothesizes the relationship between occupational factors and health behaviors by examining the theoretical link between medication adherence and job strain as characterized by an individual's physical and psychological stressors. Such physical and psychological stressors can impact a worker's confidence in his/her ability to exert control over his/her own motivation, behavior, and social environment (viz., self-efficacy) – factors that ultimately impact medication adherence. The study examines the association between job type and medication adherence in a population of individuals with diabetes and cardiovascular disease (CVD). Participants with a new or existing prescription for oral medications to treat diabetes or hyperlipidemia were enrolled into a randomized controlled trial at 34 national chain drugstores in Tennessee. Participants received standard care or a Screening and Brief Intervention (SBI) and a pillbox at the initial prescription fill, and at each additional refill, provided by a pharmacist. Medication adherence, health care utilization, psychosocial assessment, chronic disease status, and occupational health history data were obtained from the participants. Participants were then

stratified by job class and job strain. Job class was classically defined, while the Karasek demand-control model was used to characterize job strain. The Karasek model describes two components of working life that influence job strain. The first is the psychological demands of the job and the second is a worker's ability to use skills or authority to address those demands. Understanding this relationship can provide insight into the development of workplace disease prevention and wellness programs that target employees who are at increased risk for poor medication adherence as well as provide new insight to healthcare providers on the risk factors for poor adherence. Additionally, developing occupation-specific interventions to improve medication adherence may ultimately lead to a reduction in total healthcare spending.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGEMENTS

First, I would like to thank my academic advisor, James Peterson, for his continued support and for affording me the latitude to develop a research concept blending pharmaceutical science with environmental and occupational health.

I am very appreciative to committee members Nicholas Castle, Linda Pearce, and Bruce Pitt for their input into my dissertation research.

I would also like to thank committee member Janice Pringle for her expert guidance and willingness to allow the use of her randomized clinical trial as a means to explore pharmaceutical science and environmental and occupational health.

I am forever grateful to committee member Arnie Aldridge for his mentorship and scientific prowess.

I would like to recognize the following people for their assistance in making my research possible: Newell McElwee, Andi Clark, and Kim Grasso.

I would like to thank my husband, Jim, for his encouragement.

I would also like to thank my sister, Erin, for her support and editorial assistance.

I would especially like to thank my son; for the news of his impending arrival has inspired me in so many ways, especially in completing this academic endeavor.

Lastly and most importantly, I would like to thank my parents, Michael and Elisa, for instilling the importance of education. I am eternally grateful for their love and support, and to my Mom for the many science classes you enrolled me in as a kid.

DEDICATION

To my earliest educators,

Orlando DiSaia, Michael Kearney, Sr., Elizabeth Kearney,

and my parents,

Michael and Elisa Kearney

ABBREVIATIONS

BB	Beta Blockers
CCB	Calcium Channel Blockers
CVD	Cardiovascular Disease
ECO-PHIL	Effect of Community Pharmacist Intervention on adherence to Long-term medications
GLMM	Generalized Linear Mixed Models
MI	Motivational Interviewing
NIOSH	National Institute for Occupational Safety and Health
PDC	Proportion of Days Covered
PDC80	Proportion Days Covered >80%
PMPM	Per Member Per Month
PQA	Pharmacy Quality Alliance
QES	Quality of Employment Surveys
RASA	Renin Angiotensin System Antagonists
RCT	Randomized Controlled Trial
ROI	Return on Investment
SBI	Screening and Brief Intervention
SQL	Structured Query Language

1.0 INTRODUCTION

1.1 CHRONIC DISEASE

Chronic diseases such as cardiovascular disease (CVD) and diabetes are among the leading causes of death and disability in the United States, greatly affecting quality of life and healthcare costs (Bodenheimer, Chen, & Bennett, 2009; Kotecha et al., 2013; Schram, Baan, & Pouwer, 2009). Additionally, chronic disease was once thought to be a public health problem associated mainly with older age groups, however there has been a shift towards onset in the working-age population. This shift to a younger age group creates an economic burden resulting from illness-related loss of productivity due to absence from work (absenteeism) and reduced performance while at work (presenteeism) (Mattke et al., 2013). As a result, workplace wellness programs have increased in popularity via the Patient Protection and Affordable Care Act by providing health promotion and disease management programs to reduce healthcare spending (Mattke, Schnyer, & Van Busum, 2012). One important component of disease management is medication adherence – an individual's ability to comply with his or her prescribed medication regimen (Osterberg & Blaschke, 2005). Given the emerging relationship between chronic disease, work performance, and medication adherence, this dissertation will examine job class and job strain and their effect on medication adherence. Examining occupational factors may prove beneficial in developing workplace interventions that improve medication adherence,

leading to a reduction in total healthcare spending and a longer living, healthier population (Roebuck, Liberman, Gemmill-Toyama, & Brennan, 2011).

1.1.1 Resultant Healthcare Costs of Chronic Disease

As of 2012, approximately half (117 million) of US adults had one or more chronic diseases (Ward, Schiller, & Goodman, 2014). Additionally, a study by the Milken Institute calculated that seven chronic conditions (cancer, heart disease, hypertension, mental disorders, diabetes, pulmonary conditions, and stroke) are costing the US economy $1 trillion per year. Anticipated growth rates for the aforementioned conditions are expected to yield an illness burden of $4 trillion per year by 2023 (DeVol et al., 2007). The American Heart Association estimated total costs of heart disease and stroke in 2010 to be $315.4 billion (Go et al., 2014), while the total estimated cost of diagnosed diabetes in 2012 was $245 billion, including $176 billion in direct medical costs and $69 billion in decreased productivity (e.g. absenteeism, presenteeism) (American Diabetes Association, 2013). As chronic disease prevalence continues to increase, it is important to note that these diseases are often preventable and can be managed via early detection, improved diet, exercise, and disease management strategies such as medication adherence.

1.2 WORKPLACE WELLNESS

Employers have invested in workplace wellness programs to combat the chronic disease epidemic, causing workplace wellness to have increased to a $6 billion dollar industry in the

United States. In 2012, half of all employers with at least 50 employees offered workplace wellness programs, and nearly half of employers without a program indicated that they intended to introduce one (Mattke et al., 2013). Additionally, more than 60% of Americans obtain health insurance coverage through an employment-based plan, allowing them access to a workplace wellness program (Baicker, Cutler, & Song, 2010). Workplace wellness programs typically have two components: a lifestyle management program and a disease management program. The lifestyle management component focuses on employees with health risks, such as smoking and obesity, and providing support in reducing those risks to prevent the development of chronic disease. The disease management component is designed to help employees with a chronic disease to take better care of themselves via support mechanisms, such as reminding the employee to take their prescribed medications or communicating gaps in care such as missed laboratory tests, to their physicians (Mattke et al., 2013).

Applying improvement strategies to the disease management component of workplace wellness programs can result in a return on investment (ROI). The Rand Corporation found that both lifestyle and disease management programs reduced the employer's average health care costs by about $30 per member per month (PMPM) (Caloyeras, Liu, Exum, Broderick, & Mattke, 2014; Mattke et al., 2013). However, the disease management program alone was responsible for 87% of those savings. Employees participating in the disease management program generated a savings of $136 PMPM, largely due to a 30% reduction in hospital admissions. While a smaller percentage of employees may participate in a disease management program, the ROI is far greater than those employees that participate in a lifestyle management program. Strategizing approaches to improve medication adherence within the workforce can

provide a successful way to reach individuals that are not adherent and further improve the effectiveness of disease management (Carls et al., 2012; Loeppke et al., 2011).

1.3 MEDICATION ADHERENCE

Medication adherence, the compliance with a medication regimen, is generally defined as the extent to which individuals take medications as prescribed by their health care providers. Improving medication adherence is critical as medication non-adherence is a major problem in the management of chronic diseases. Approximately, 20% – 50% of individuals do not take their medications as prescribed (Kripalani, Yao, & Haynes, 2007) and inadequate adherence has been estimated to contribute to $290 billion in unnecessary healthcare costs (Network for Excellence in Health Innovation, 2011). Furthermore, there is no single intervention strategy shown to be effective across all individuals, conditions, and settings (World Health Organization, 2010). Therefore, strategies that improve medication adherence should be tailored to each individual as medication adherence ultimately reduces total annual health care spending (Dimatteo, Giordani, Lepper, & Croghan, 2002; Goetzel et al., 2004; Iuga & McGuire, 2014; Roebuck et al., 2011; Sokol, McGuigan, Verbrugge, & Epstein, 2005).

1.4 DISSERTATION OBJECTIVES

This study hypothesizes for the first time the relationship between occupational factors and health behaviors by examining the theoretical link between job type and medication

adherence as characterized by an individual's job strain and physical and psychological stressors. Such physical and psychological stressors can impact confidence in the ability to exert control over one's own motivation, behavior, and social environment (viz., self-efficacy) – factors that ultimately determine medication adherence (Kobau & DiIorio, 2003; Luszczynska, Sarkar, & Knoll, 2007).

Chapter 1 introduces the relationship between chronic diseases, healthcare costs, workplace wellness, and medication adherence.

Chapter 2 describes the hypothesized theoretical model, examining the influence of occupational factors (e.g. job class and job strain), physical and psychological stress, and self-efficacy on the relationship between job type and medication adherence.

Chapter 3 reviews the rigorous methodology involved with this prospective research study. The study design is presented, along with the occupational questionnaire, characterization of occupational factors (e.g. job class and job strain), the intervention (Screening and Brief Intervention (SBI) + pillbox) utilized to improve medication adherence, and the measurement, proportion days covered (PDC), used to evaluate medication adherence. Lastly, the statistical methods are presented and encompass data collection, covariates used in each model, and the modeling method, Generalized Linear Mixed Models (GLMM).

In Chapter 4, the results are presented as pre-intervention models (i.e. baseline results) and intervention moderator models (i.e. models that characterize the intervention's effect on medication adherence) using GLMM. GLMM, controlling for demographics, marital status, education, employment status, income, and baseline measures of health were used to conclude that occupational factors such as job strain moderate medication adherence.

Chapter 5 provides a discussion of the pre-intervention and the intervention moderator model results.

Lastly, Chapter 6 summarizes the overall scientific contribution of this research study to the field of public health with proposed actions for further research.

By examining the effects of occupational history on medication adherence in a population of individuals with diabetes and CVD, a theoretical link between job type and medication adherence might be associated with occupational factors (e.g. job class and job strain). Understanding this relationship can provide insight into the development of workplace disease prevention and wellness programs that target employees who are at increased risk for poor medication adherence. Thus, leading to slower disease progression, reduced mortality, and decreased healthcare costs.

2.0 THEORETICAL MODEL

This study hypothesizes the relationship between job type and medication adherence by examining occupational factors (e.g. job class and job strain) associated with medication adherence. This relationship is characterized by Figure 1.

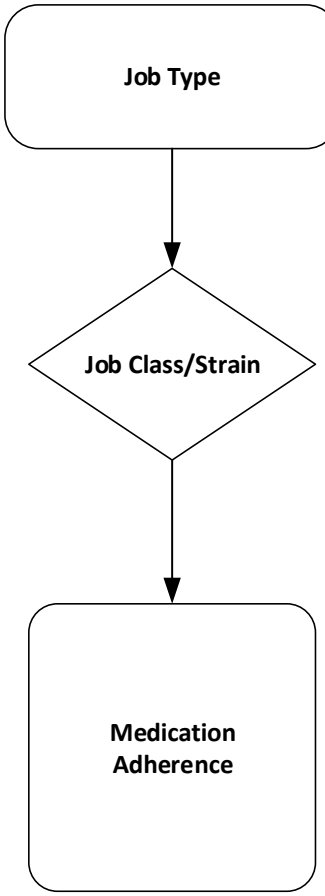

Figure 1. Theoretical Model

Job class and job strain are used to characterize job type. Job class is classically defined as manual (blue-collar), nonmanual (white-collar), or not working (retired, disabled, and unemployed). Job strain is characterized by Karasek's demand-control model, where strain is defined as either active (high psychological demand, high decision latitude), high strain (high psychological demand, low decision latitude), low strain (low psychological demand, high decision latitude), passive (low psychological demand, low decision latitude), or non-contributing (unemployed, disabled, and retired). In Figure 1, both job class and job strain serve as mediator variables in the relationship between job type and medication adherence (Baron & Kenny, 1986). Job class and job strain are considered mediating variables as they are determinants that explain why a particular effect occurs between two variables (e.g. job type and medication adherence). Both strain and class can explain how external factors such as job stress influence psychological associations such as adherence to a prescribed medication regimen (Baron & Kenny, 1986; Diestel & Schmidt, 2009). Psychological factors including job autonomy, self-efficacy, an individual's belief in his or her capacity to execute behaviors necessary to produce specific performance attainments, and learned helplessness, when an individual lacks the requisite controlling response in a situation but believes this response is available to others, can affect an individual's performance in achieving a desired health outcome (Bandura, 1977, 1986, 1997; Strecher, DeVellis, Becker, & Rosenstock, 1986).

The *Theoretical Model* can be further expounded to the hypothesized *Pre-Intervention Theoretical Model* depicted in Figure 2. Physical/psychological stress and self-efficacy are additional determinants that should be considered in the relationship between job type and medication adherence. It is hypothesized that stress may have a direct mediational effect on adherence, which does not operate through self-efficacy as illustrated by Figure 2. As a

mediator, physical/psychological stress can directly affect the relationship between job type and an individual's ability to perform a health behavior such as medication adherence (Bijl, Van Zessen, Ravelli, De Rijk, & Langendoen, 1998; Diestel & Schmidt, 2009). As a moderator, physical/psychological stress can influence the strength of the relationship between job type and self-efficacy in relation to medication adherence (Baron & Kenny, 1986). In essence, physical/psychological stress can serve as both a mediator, to explain why there is a relationship, and a moderator, to discern the extent of the influencing effect of this relationship.

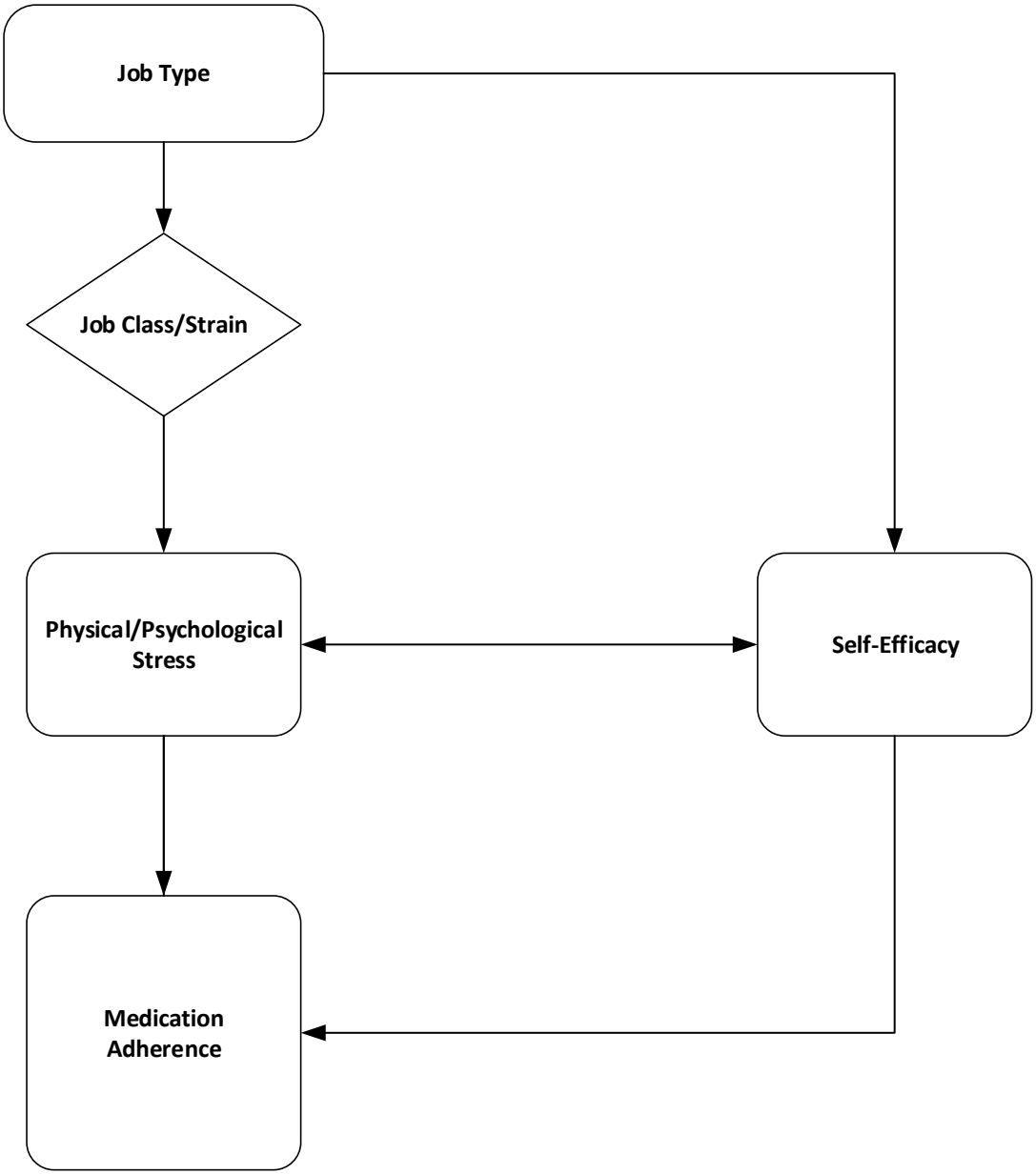

Figure 2. Pre-Intervention Theoretical Model

Figure 3, *Intervention Moderator Theoretical Model* applies the intervention (SBI + pill box), illustrating the hypothesis examined in this dissertation where occupational factors are moderators of the intervention effect on medication adherence. Job class and job strain are considered moderators in this model since their interaction with physical/psychological stress and self-efficacy may explain the degree of adherence in relation to the intervention.

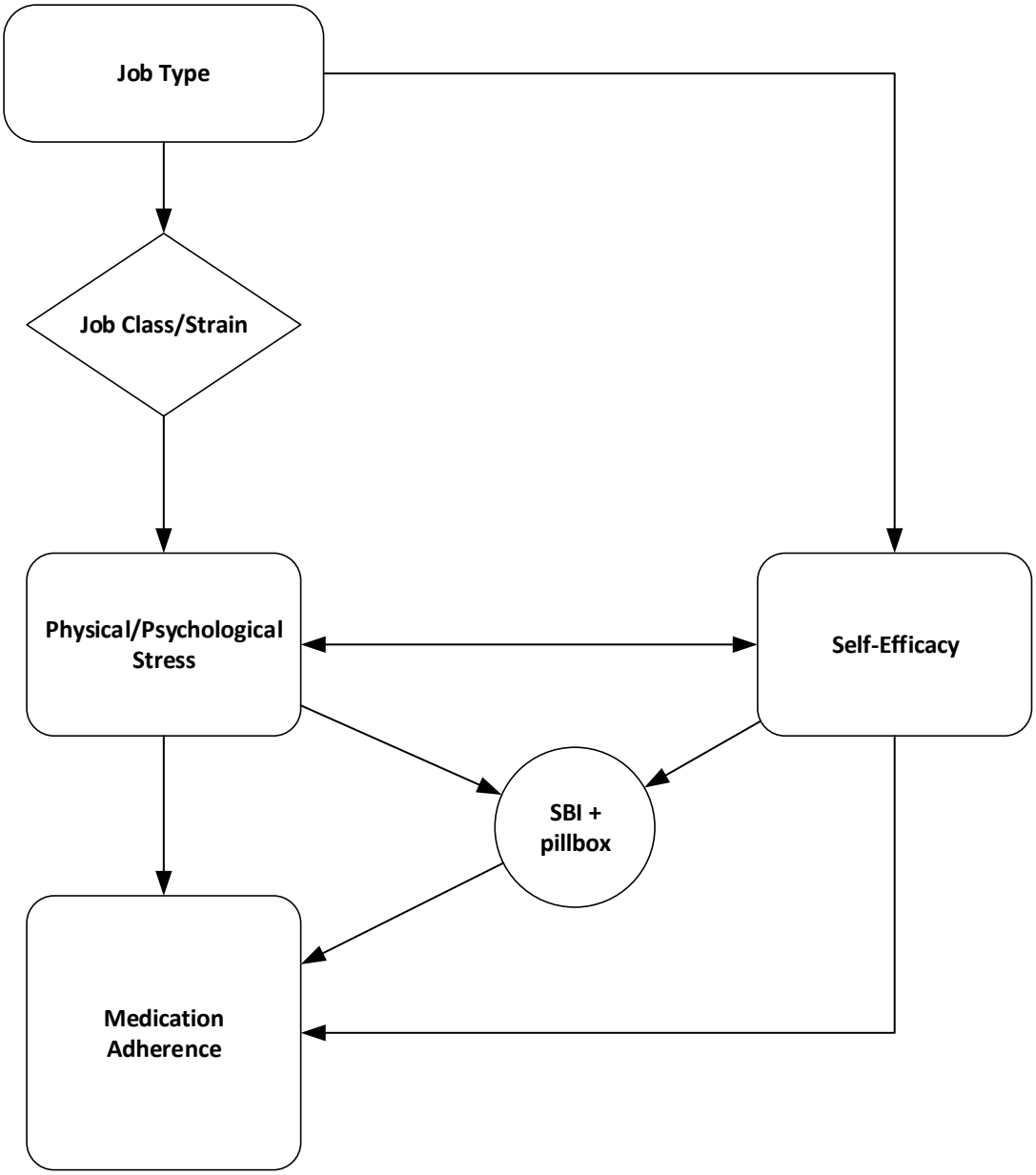

Figure 3. Intervention Moderator Theoretical Model

Occupational factors such as job class and job strain, physical and psychological stress, and self-efficacy will be further described in the subsequent sections of this chapter. Each determinant plays a specific role in understanding the relationship between job type and medication adherence.

2.1 JOB STRAIN

The job strain model first postulated by Robert A. Karasek, Jr. has become a widely accepted and applied model (Belkic, Landsbergis, Schnall, & Baker, 2004; De Lange, Taris, Kompier, Houtman, & Bongers, 2003; Goldberg, Gueguen, Schmaus, Nakache, & Goldberg, 2001; Häusser, Mojzisch, Niesel, & Schulz-Hardt, 2010; Hellerstedt & Jeffery, 1997; Houtman et al., 1999; R. A. Karasek et al., 1988; Kivimäki et al., 2012; Lerner, Levine, Malspeis, & D'Agostino, 1994; Pelfrene et al., 2001; Schnall, Landsbergis, & Baker, 1994; Törnroos et al., 2015). The job strain model, often referred to as the demand-control model, proposes that job strain is not attributed to a single aspect of the work environment, but from the joint effects of the demands of a work situation and the range of decision-making freedom or discretion available to the worker facing those demands (i.e. job autonomy) (Karasek Jr, 1979). These two aspects of an occupation represent, respectively, action (work load demands, conflicts or other stressors which place the individual in a motivated or energized state of "stress") and the constraints on the alternative resulting actions (Karasek Jr, 1979). The individual's job decision latitude is the constraint which modulates the release or transformation of "stress" potential energy into the energy of action (Karasek Jr, 1979).

While Karasek's job strain model has been applied to a number of studies, the model is often attributed to CVD research and demonstrates that job strain has an impact on cardiovascular health (Collins, Karasek, & Costas, 2005; Hellerstedt & Jeffery, 1997; R. Karasek, Baker, Marxer, Ahlbom, & Theorell, 1981; R. Karasek, Collins, Clays, Bortkiewicz, & Ferrario, 2010; Landsbergis, Schnall, Schwartz, Warren, & Pickering, 1995; Schnall et al., 1994; Schnall et al., 1990; Steenland et al., 2000; Theorell & Karasek, 1996). High strain (high

psychological demand, low decision latitude) job types have been found to be negatively associated with health, while active (high psychological demand, high decision latitude) and low strain (low psychological demand, high decision latitude) job types are positively associated with health (Lerner et al., 1994). Passive (low psychological demand, low decision latitude) job types fall within the spectrum. Not only does the addition of job strain to the hypothesized models allow the use of a widely accepted tool for characterizing job type, but the job strain model is also appropriate as the prospective research study presented in this dissertation examines a population of individuals with CVD and diabetes.

Job strain acts as a mediator in the *Pre-Intervention Theoretical Model* accounting for the relation between job type and medication adherence. Job strain characterizes job type in terms of physical/psychological factors which can impact an individual outside of the workplace. As a mediating variable, job strain explains how external factors such as job stress can cause a particular effect to occur (i.e. adherence to a prescribed medication regimen) (Baron & Kenny, 1986; Diestel & Schmidt, 2009). In the *Intervention Moderator Theoretical Model*, job strain becomes a moderator of the relationship between job type and medication adherence, affecting the magnitude of the intervention's effect on medication adherence. Ultimately, job strain is hypothesized to be a key determinant in the relationship between job type and medication adherence.

2.2 PHYSICAL AND PSYCHOLOGICAL STRESS

The National Institute for Occupational Safety and Health (NIOSH) states that job stress can be defined as the harmful physical and emotional responses that occur when the

requirements of the job do not match the capabilities, resources, or needs of the worker (Sauter et al.). Exposure to stressful working conditions or job stressors can directly affect a worker's safety and health. These factors are presented in both the *Pre-Intervention Theoretical Model* and *Intervention Moderator Theoretical Model*.

Physical and psychological stressors have been shown to evoke biological responses that cause a predisposition to disease or poor health outcomes by a variety of mechanisms via the nervous, cardiovascular, endocrine, and immune systems (Schneiderman, Ironson, & Siegel, 2005). Studies have shown both acute and chronic biological responses to stress. For example, increased cortisol levels (Schulz, Kirschbaum, Prüßner, & Hellhammer, 1998), activation of cellular responses by the immune system (Dhabhar & Mcewen, 1997), and cardiovascular responses such as increased blood pressure (Vrijkotte, Van Doornen, & De Geus, 2000). Psychosocial stressors have also been extensively studied and linked to disease. For example, psychosocial stressors, such as job strain, anxiety, and stress have been linked to CVD (Houtman et al., 1999; R. Karasek et al., 1981; R. A. Karasek et al., 1988; Kivimäki et al., 2012; Rozanski, Blumenthal, & Kaplan, 1999).

Physical/psychological stress serves as a mediator in the relationship between job type and medication adherence in that physical and psychological stressors can have a direct impact on an individual's ability to adhere to their prescribed medication regimen. Self-efficacy, an individual's confidence in his/her ability to exert control over his/her own motivation, behavior, and social environment, affects an individual's self-regulation of disease prevention and management (Clark & Dodge, 1999). Physical/psychological stress can act as a moderator of self-efficacy in the relationship between job type and medication adherence in that it moderates an individual's ability to perform a health behavior such as compliance to their prescribed

medication regimen (Grau, Salanova, & Peiro, 2001). Additionally, physical/psychological stress are impacted by job strain and can affect an individual's ability to perform a desired health behavior (Jex & Bliese, 1999; Jex & Gudanowski, 1992).

It is also important to note that a reciprocal relationship exists between physical and psychological stress. For example, physical stressors may cause a proclivity to psychological stressors (e.g. lack of autonomy may cause disengagement by an employee yielding anxiety) and psychological stressors may manifest as physical stressors (e.g. anxiety due to work overload can result in exhaustion) (Cohen, Janicki-Deverts, & Miller, 2007; Cohen, Kessler, & Gordon, 1995). Physical/psychological stress is hypothesized as a key determinant in both the pre-intervention and intervention moderator theoretical models as it can play a role, respectively or mutually, in the relationship between job type and health behaviors (i.e. medication adherence) (Blair, Jacobs Jr, & Powell, 1985; Cooper & Cartwright, 1994; DeLongis, Folkman, & Lazarus, 1988; Ng & Jeffery, 2003).

2.3 SELF-EFFICACY

Self-efficacy refers to an individual's belief in his or her capacity to execute behaviors necessary to produce specific performance attainments (Bandura, 1977, 1986, 1997). Often analyzed as a determinant of health behavior change (AbuSABHA & Achterberg, 1997; Bandura, 1990; DiClemente, Fairhurst, & Piotrowski, 1995; Kelly, Zyzanski, & Alemagno, 1991; O'Leary, 1985; Strecher et al., 1986), self-efficacy is the result of the interaction of personal, behavioral and environmental factors (Clark & Dodge, 1999).

In Figures 2 and 3, *Pre-Intervention Theoretical Model* and *Intervention Moderator Theoretical Model*, respectively, it is hypothesized that self-efficacy mediates the relationship between job type and medication adherence (Brown & Bussell, 2011; Judge & Bono, 2001; Schaubroeck & Merritt, 1997). Additionally, self-efficacy has become a key construct in developing interventions to improve chronic disease outcomes (e.g. interventions that improve medication adherence) (Herrick, Stone, & Mettler, 1997; Marks & Allegrante, 2005). Therefore, self-efficacy is hypothesized as a key determinant in the relationship between job type and medication adherence, in that it can affect physical/psychological stress.

3.0 METHODS

3.1 STUDY DESIGN

The participants in this study were participants of the randomized controlled trial (RCT), *Effect of Community Pharmacist Intervention on adherence to Long-term medications*, (ECO-PHIL) study. Individuals with a new or existing prescription for oral medications and a diagnosis of diabetes or hyperlipidemia were enrolled into the trial at one of 34 drugstores of a national pharmacy chain in Tennessee.

Participants were randomized via permuted block design into one of two groups; standard care treatment group and intervention treatment group. The standard care treatment group received care as usual by the pharmacist. The intervention treatment group (SBI + pillbox) received both a Screening and Brief Intervention (SBI) and a pillbox based upon motivational interviewing principles at the initial prescription fill, and at each additional refill. Additional inclusion criteria required that participants be 30 – 85 years of age, comfortable speaking English, not institutionalized, and not diagnosed with psychosis or dementia. Medication adherence, occupational health history, health care utilization, psychosocial assessment, and chronic disease status data from participants were obtained. Medication adherence data were drawn from pharmacy claims data, covering a period of one year before each participant's

enrollment date into the study and at the conclusion of their involvement with the study. Occupational health history was collected through a self-report questionnaire (Appendix A).

Participants were then stratified by job class and job strain. Lastly, GLMM, controlling for demographics, marital status, education, employment status, income, and baseline measures of health were used to conclude that occupational factors exhibit a moderating effect on medication adherence.

3.2 OCCUPATIONAL HEALTH QUESTIONNAIRE

Participants (n=506) were administered an occupational health questionnaire (Appendix A) devised from the Economic Form 90, an instrument used to assess economic outcomes, and tailored to this study population (Bray et al., 2007). The University of Pittsburgh Institutional Review Board provided approval and oversight of this study, IRB# MOD12050040-03/PRO12050040, *Prospective Study on a Pharmacist-led Intervention to Improve Medication Adherence* (Appendix B). Participants were asked to report via self-addressed stamped envelope or telephonic interview: 1) their job title or most recent job title if they were not currently working; 2) their job setting or most recent job setting if they were not currently working; and 3) their current income range or prior income range if they were not currently working. The reported job title and job setting were used to characterize each participant's job type by job class and job strain.

3.3 CHARACTERIZATION OF OCCUPATIONAL FACTORS

Participants were stratified by job class and job strain. Job class was classically defined and divided into three categories: manual (blue-collar), nonmanual (white-collar), and not working (retired, disabled, and unemployed). Job strain was characterized by Karasek's demand-control model. This model describes two dimensions of working life that influence job strain: the psychological demands of the job and the worker's ability to use skills or authority to address those demands (i.e. decision latitude) (Hellerstedt & Jeffery, 1997).

Job strain was divided into five categories. The first four categories are based on the Karasek model: active (high psychological demand, high decision latitude), high strain (high psychological demand, low decision latitude), low strain (low psychological demand, high decision latitude), and passive (low psychological demand, low decision latitude). A fifth category was created and termed 'non-contributing', containing a combination of unemployed, disabled, and retired participants. The participant's job type was matched to the appropriate job strain using the *Occupational Distribution of Psychosocial Job Characteristics* (Appendix C) created from the US Department of Labor Quality of Employment Surveys (QES) of the full work force in 1969, 1972, and 1977 (R. A. Karasek et al., 1988).

3.4 THE INTERVENTION

Participants randomized into the intervention group (SBI + pillbox) received both a pillbox and a Screening and Brief Intervention (SBI) based upon motivational interviewing principles at the initial prescription fill, and at each subsequent refill. The pillbox served as a

passive reminder for the participant to adhere to their medication regimen. The SBI served as the active approach.

The SBI is a brief 2 – 5 minute conversation led by the pharmacist using motivational interviewing (MI) principles to address specific issues that may affect an individual's initial and continued use of their prescribed medication regimen. MI employs the use of open-ended questions, appropriate affirmations, and reflective listening, as an individual is guided through a process where they can explore and understand the barriers to changing their behavior and identify strategies to help them overcome those barriers (Miller & Rollnick, 2002). MI has been used to address a number of other health behaviors including tobacco cessation, diet and exercise, diabetes self-management, oral health (Martins & McNeil, 2009), mental health (Rollnick, Miller, & Butler, 2008), sexual health (Petersen, Albright, Garrett, & Curtis, 2007), and chronic pain (Rau, Ehlebracht-König, & Petermann, 2008).

The RCT utilized a paradigm developed by the study's Principal Investigator called POLAR*S™. POLAR*S is an acronym for the following application of motivational interviewing: Permission (P), Open-ended questions (O), Reflective Listening (L), Affirmation (A), Roll with Resistance (R), and Summary (S). Pharmacists were trained in the use of the adherence-focused brief intervention designed for a typical community pharmacy setting. The paradigm has been reported to be helpful in both initiating and completing an SBI with any given individual (Pringle, Boyer, Conklin, McCullough, & Aldridge, 2014).

3.5 MEASUREMENT OF ADHERENCE: PDC

Medication adherence was measured as proportion of days covered (PDC) using the Pharmacy Quality Alliance's (PQA) convention which includes a set of National Drug Codes (NDCs) for five classes of chronic disease medications: beta blockers (BB), calcium channel blockers (CCB), diabetes, renin angiotensin system antagonists (RASA), and statins. PDC is calculated as the total number of days an individual is supplied a medication during an interval divided by the total number of days during that interval (Iuga & McGuire, 2014). Most participants enrolled in the study were taking more than one of the specified medication classes. Therefore, in addition to each individual class, variables were constructed based on these five classes to measure different aspects of a participant's overall behavior (e.g. their average adherence across all relevant classes). Adherence measures were constructed from pharmacy claims data provided by the national drugstore chain. PDC and PDC80, a benchmark measurement for >80% of days covered, were estimated as continuous variables. For example, binary PDC80 outcomes were estimated as a linear probability model.

3.6 STATISTICAL ANALYSIS

3.6.1 Data Collection

Participant enrollment began July 2, 2012 and concluded on April 27, 2013. Upon enrollment, participants were asked to complete a baseline interview conducted by research personnel for the collection of chronic disease status, health care utilization, and psychosocial

assessment data. Follow-up interviews were also conducted at six and nine month intervals, respectively, for the collection of occupational health data in addition to baseline information. Medication adherence data via administrative claims data was obtained for a time period of one year prior to the participant's enrollment date in the RCT through the final nine month follow-up interview.

Performance metrics were developed for various study activities including the completion of participant interviews, ascertainment of medical records, and entry of the data collected. To ensure fidelity of the SBIs for those participants randomized into the intervention treatment group, pharmacists completed standard forms to document their SBI with participants each time they presented at the pharmacy for a prescription refill. This documentation was then sent to the research team and added to the study file for each participant. Weekly quality improvement meetings were held among research staff to address any obstacles in reaching the established data metrics. Participant enrollment forms and study questionnaires were checked for completeness and accuracy. Discrepant or missing data were resolved using several techniques, including the review of other study documents that contained similar information, communicating with the pharmacy that enrolled the participant, or communicating with the participant directly.

A data review was conducted monthly by research personnel on a 10% random sample of the data collected. The established quality metric of 98% data accuracy (a comparison of data being entered into the Structured Query Language (SQL) database against the original data source) was reached continually for each data domain. If data were found to be discrepant against the data source, verified data changes were entered into the SQL database with appropriate documentation. Systemic issues (such as conventions for determining dates) that

may have resulted in data entry errors were addressed in the weekly quality improvement meetings and process changes were made to resolve these errors.

3.6.2 Covariates

To examine the associations with medication adherence, analyses controlled for demographics, marital status, education status, employment status, income, and baseline measures of health. Baseline measures of health included diabetes diagnosis, cholesterol diagnosis, heart disease diagnosis, hypertension diagnosis, stroke diagnosis, depression diagnosis, and an indicator for any other chronic disease diagnosis. Employment status was characterized as full-time, part-time, retired, disabled, and unemployed. Current and prior income was classified by the following ranges and treated as a continuous variable: $0 – $15,000, $15,001 – $30,000, $30,001 – $50,000, $50,001 – $75,000, $75,001 – $100,000, and more than $100,000. Covariates were used in one of two models. The first model or pre-intervention model analyzes PDC at baseline for job class and job strain. The second model or intervention moderator model estimates how job class and job strain influence the intervention's effect on PDC. Table 1 summarizes the covariates used in the pre-intervention models, while Table 2 presents the covariates used in the intervention moderator models. Pairwise t-tests are included for key variables by job class and job strain in Appendix D.

Table 1. Pre-Intervention Model Variables

Variable	Description
disease	Proportion of individuals with Diabetes, indicator variable (0 if not present, 1 if present)
pdc	Proportion Days Covered (PDC), continuous variable
pdcmbb0	Proportion Days Covered (PDC) for beta blockers (BB) medication class pre-intervention, continuous variable
pdcmccb0	Proportion Days Covered (PDC) for calcium channel blockers (CCB) medication class pre-intervention, continuous variable
pdcmdiab0	Proportion Days Covered (PDC) for diabetes medication class

Table 1 continued

Variable	Description
	pre-intervention, continuous variable
pdcmrasa0	Proportion Days Covered (PDC) for renin angiotensin system antagonists (RASA) medication class pre-intervention, continuous variable
pdcmstat0	Proportion Days Covered (PDC) for statins medication class, pre-intervention, continuous variable
pdc80bb0	Proportion Days Covered >80% (PDC80) for beta blockers (BB) medication class pre-intervention, indicator variable (0 if not present, 1 if present)
pdc80ccb0	Proportion Days Covered >80% (PDC80) for calcium channel blockers (CCB) medication class pre-intervention, indicator variable (0 if not present, 1 if present)
pdc80diab0	Proportion Days Covered >80% (PDC80) for diabetes medication class pre-intervention, indicator variable (0 if not present, 1 if present)
pdc80raas0	Proportion Days Covered >80% (PDC80) for renin angiotensin system antagonists (RASA) medication class pre-intervention, indicator variable (0 if not present, 1 if present)
pdc80stat0	Proportion Days Covered >80% (PDC80) for statins medication class pre-intervention, indicator variable (0 if not present, 1 if present)
mdage	Age, continuous variable
mdf	Female, indicator variable (0 if not present, 1 if present)
mdnonwh	Non-white, indicator variable (0 if not present, 1 if present)
mdedm1	Individual has less than a high school degree, indicator variable (0 if not present, 1 if present)
mdedm2	Individual has a high school degree, indicator variable (0 if not present, 1 if present)
mdedm3	Individual has a four-year degree, indicator variable (0 if not present, 1 if present)
mdedm4	Individual has a professional/graduate level degree, indicator variable (0 if not present, 1 if present)
mdmarpar	Individual is married/partnered, indicator variable (0 if not present, 1 if present)
mdlivhom	Independent living, indicator variable (0 if not present, 1 if present)
mdemp1	Employed full-time, indicator variable (0 if not present, 1 if present)
mdemp2	Employed part-time, indicator variable (0 if not present, 1 if present)
mdemp3	Retired, indicator variable (0 if not present, 1 if present)
mdemp4	Disabled, indicator variable (0 if not present, 1 if present)
mdemp5	Not employed, indicator variable (0 if not present, 1 if present)
incc1	Current income between $0 - $15,000, continuous variable
incc2	Current income between $15,001 - $30,000, continuous variable
incc3	Current income between $30,001 - $50,000, continuous variable
incc4	Current income between $50,001-$75,000, continuous variable
incc5	Current income between $75,001-$100,000, continuous variable
incc6	Current income is more than $100,000, continuous variable
incp1	Prior income is between $0 - $15,000, continuous variable
incp2	Prior income is between $15,001 - $30,000, continuous variable
incp3	Prior income is between $30,001 - $50,000, continuous variable
incp4	Prior income is between $50,001 - $75,000, continuous variable

Table 1 continued

Variable	Description
incp5	Prior income is between $75,001 - $100,000, continuous variable
incp6	Prior income is more than $100,000, continuous variable
mdbins1	Insured via individual plan, indicator variable (0 if not present, 1 if present)
mdbins2	Insured via group plan, indicator variable (0 if not present, 1 if present)
mdbins3	Insured via military/government, indicator variable (0 if not present, 1 if present)
mdbins4	Insured via Medicaid, indicator variable (0 if not present, 1 if present)
mdbins5	Insured via Medicare, indicator variable (0 if not present, 1 if present)
mdbins6	Not insured, indicator variable (0 if not present, 1 if present)
mddxdiab	Diabetes diagnosis, indicator variable (0 if not present, 1 if present)
mddxchol	Cholesterol diagnosis, indicator variable (0 if not present, 1 if present)
mddxhrtd	Heart disease diagnosis, indicator variable (0 if not present, 1 if present)
mddxbp	Hypertension diagnosis, indicator variable (0 if not present, 1 if present)
mddxstrk	Stroke diagnosis, indicator variable (0 if not present, 1 if present)
mddxdepr	Depression diagnosis, indicator variable (0 if not present, 1 if present)
mddxothe	Other chronic disease diagnosis, indicator variable (0 if not present, 1 if present)
mddrqs1	When you visit your doctor, how often do you prepare a list of questions for your doctor?, continuous variable (1 = never to 6 = always)
mddrqs2	When you visit your doctor, how often do you ask questions about the things you don't understand about your treatment?, continuous variable (1 = never to 6 = always)
mddrqs3	When you visit your doctor, how often do you discuss any personal problems that may be related to your illness?, continuous variable (1 = never to 6 = always)
mdhealth	In general, you would say your health is?, continuous variable (1 = excellent to 5 = poor)

Table 2. Intervention Moderator Model Variables

Variable	Description
disease	Proportion of individuals with Diabetes, indicator variable (0 if not present, 1 if present)
pdc	Proportion Days Covered (PDC), continuous variable
pdcmbb0	Proportion Days Covered (PDC) for beta blockers (BB) medication class pre-intervention, continuous variable
pdcmbb1	Proportion Days Covered (PDC) for beta blockers (BB) medication class post-intervention, continuous variable
pdcmccb0	Proportion Days Covered (PDC) for calcium channel blockers (CCB) medication class pre-intervention, continuous variable
pdcmccb1	Proportion Days Covered (PDC) for calcium channel blockers (CCB) medication class post-intervention, continuous variable
pdcmdiab0	Proportion Days Covered (PDC) for diabetes medication class pre-intervention, continuous variable
pdcmdiab1	Proportion Days Covered (PDC) for diabetes medication class

Table 2 continued

Variable	Description
	post-intervention, continuous variable
pdcmrasa0	Proportion Days Covered (PDC) for renin angiotensin system antagonists (RASA) medication class pre-intervention, continuous variable
pdcmraas1	Proportion Days Covered (PDC) for renin angiotensin system antagonists (RASA) medication class post-intervention, continuous variable
pdcmstat0	Proportion Days Covered (PDC) for statins medication class, pre-intervention, continuous variable
pdcmstat1	Proportion Days Covered (PDC) for statins medication class, post-intervention, continuous variable
pdc80bb0	Proportion Days Covered >80% (PDC80) for beta blockers (BB) medication class pre-intervention, indicator variable (0 if not present, 1 if present)
pdc80bb1	Proportion Days Covered >80% (PDC80) for beta blockers (BB) medication class post-intervention, indicator variable (0 if not present, 1 if present)
pdc80ccb0	Proportion Days Covered >80% (PDC80) for calcium channel blockers (CCB) medication class pre-intervention, indicator variable (0 if not present, 1 if present)
pdc80ccb1	Proportion Days Covered >80% (PDC80) for calcium channel blockers (CCB) medication class post-intervention, indicator variable (0 if not present, 1 if present)
pdc80diab0	Proportion Days Covered >80% (PDC80) for diabetes medication class pre-intervention, indicator variable (0 if not present, 1 if present)
pdc80diab1	Proportion Days Covered >80% (PDC80) for diabetes medication class pre-intervention, indicator variable (0 if not present, 1 if present)
pdc80raas0	Proportion Days Covered >80% (PDC80) for renin angiotensin system antagonists (RASA) medication class pre-intervention, indicator variable (0 if not present, 1 if present)
pdc80raas1	Proportion Days Covered >80% (PDC80) for renin angiotensin system antagonists (RASA) medication class post-intervention, indicator variable (0 if not present, 1 if present)
pdc80stat0	Proportion Days Covered >80% (PDC80) for statins medication class pre-intervention, indicator variable (0 if not present, 1 if present)
pdc80stat1	Proportion Days Covered >80% (PDC80) for statins medication class post-intervention, indicator variable (0 if not present, 1 if present)
mdage	Age, continuous variable
mdf	Female, indicator variable (0 if not present, 1 if present)
mdnonwh	Non-white, indicator variable (0 if not present, 1 if present)
mdedm1	Individual has less than a high school degree, indicator variable (0 if not present, 1 if present)
mdedm2	Individual has a high school degree, indicator variable (0 if not present, 1 if present)
mdedm3	Individual has a four-year degree, indicator variable (0 if not present, 1 if present)
mdedm4	Individual has a professional/graduate level degree, indicator variable (0 if not present, 1 if present)
mdmarpar	Individual is married/partnered, indicator variable (0 if not present, 1 if present)
mdlivhom	Independent living, indicator variable (0 if not present, 1 if present)
mdemp1	Employed full-time, indicator variable (0 if not present, 1 if present)
mdemp2	Employed part-time, indicator variable (0 if not present, 1 if

Table 2 continued

Variable	Description
	present)
mdemp3	Retired, indicator variable (0 if not present, 1 if present)
mdemp4	Disabled, indicator variable (0 if not present, 1 if present)
mdemp5	Not employed, indicator variable (0 if not present, 1 if present)
incc1	Current income between $0 - $15,000, continuous variable
incc2	Current income between $15,001 - $30,000, continuous variable
incc3	Current income between $30,001 - $50,000, continuous variable
incc4	Current income between $50,001-$75,000, continuous variable
incc5	Current income between $75,001-$100,000, continuous variable
incc6	Current income is more than $100,000, continuous variable
incp1	Prior income is between $0 - $15,000, continuous variable
incp2	Prior income is between $15,001 - $30,000, continuous variable
incp3	Prior income is between $30,001 - $50,000, continuous variable
incp4	Prior income is between $50,001 - $75,000, continuous variable
incp5	Prior income is between $75,001 - $100,000, continuous variable
incp6	Prior income is more than $100,000, continuous variable
mdbins1	Insured via individual plan, indicator variable (0 if not present, 1 if present)
mdbins2	Insured via group plan, indicator variable (0 if not present, 1 if present)
mdbins3	Insured via military/government, indicator variable (0 if not present, 1 if present)
mdbins4	Insured via Medicaid, indicator variable (0 if not present, 1 if present)
mdbins5	Insured via Medicare, indicator variable (0 if not present, 1 if present)
mdbins6	Not insured, indicator variable (0 if not present, 1 if present)
mddxdiab	Diabetes diagnosis, indicator variable (0 if not present, 1 if present)
mddxchol	Cholesterol diagnosis, indicator variable (0 if not present, 1 if present)
mddxhrtd	Heart disease diagnosis, indicator variable (0 if not present, 1 if present)
mddxbp	Hypertension diagnosis, indicator variable (0 if not present, 1 if present)
mddxstrk	Stroke diagnosis, indicator variable (0 if not present, 1 if present)
mddxdepr	Depression diagnosis, indicator variable (0 if not present, 1 if present)
mddxothe	Other chronic disease diagnosis, indicator variable (0 if not present, 1 if present)
mddrqs1	When you visit your doctor, how often do you prepare a list of questions for your doctor?, continuous variable (1 = never to 6 = always)
mddrqs2	When you visit your doctor, how often do you ask questions about the things you don't understand about your treatment?, continuous variable (1 = never to 6 = always)
mddrqs3	When you visit your doctor, how often do you discuss any personal problems that may be related to your illness?, continuous variable (1 = never to 6 = always)
mdhealth	In general, you would say your health is?, continuous variable (1 = excellent to 5 = poor)

3.6.3 Generalized Linear Mixed Models

Multivariate statistics were examined using GLMM. GLMM allow response variables from different distributions, such as binary responses and includes both fixed and random effects, hence mixed models. The general linear form of the model, in matrix notation, is shown in equation 1:

$$\mathbf{y = X\beta + Z\gamma + \varepsilon + \varepsilon,} \quad (1)$$

where X is the fixed effects or covariates and Z is the random effects or individuals nested within pharmacies.

Models were created for PDC as a function of job class and job strain, respectively, and are presented in the following equations for pre-intervention and intervention moderator models.

The pre-intervention model depicting PDC at baseline for job class is shown in equation 2:

$$\mathbf{PDC_{i,\,m} = \beta_o + \beta_1 JOB\ CLASS_i + X_i\beta_2 + \varepsilon_p + \varepsilon_i,} \quad (2)$$

where $PDC_{i,\,m}$ is the proportion days covered by individual (i) and medication class (m), β_o is the intercept, β_1 is the set of coefficients for each of the job class indicator variables, JOB $CLASS_i$ is a set of indicator variables classified as manual (blue-collar), nonmanual (white-collar), or not working (retired, disabled, and unemployed) by individual (i), X_i represents all other covariates in the model at the individual (i) level, β_2 is the set of coefficients for the covariates, ε_p is the model prediction error by pharmacy (p) and ε_i is the model prediction error by individual (i).

The pre-intervention model representing PDC at baseline for job strain is shown in equation 3:

$$\mathbf{PDC}_{i,\,m} = \beta_0 + \beta_1\mathbf{JOB\ STRAIN}_i + \mathbf{X}_i\beta_2 + \varepsilon_p + \varepsilon_i, \quad (3)$$

where $PDC_{i,\,m}$ is the proportion days covered by individual (i) and medication class (m), β_o is the intercept, β_1 is the set of coefficients for each of the job strain indicator variables, JOB $STRAIN_i$ is a set of indicator variables classified as active, high strain, low strain, passive, and non-contributing by individual (i), X_i represents all other covariates in the model at the individual (i) level, β_2 is the set of coefficients for the covariates, ε_p is the model prediction error by pharmacy (p) and ε_i is the model prediction error by individual (i).

The intervention moderator model demonstrating the intervention's effect on PDC in relation to job class is shown in equation 4:

$$\mathbf{PDC}_i = \beta_0 + \beta_1\ \mathbf{JOB\ CLASS}_i + \beta_2\mathbf{INTERVENTION} + \beta_3\mathbf{JOB\ CLASS*INTERVENTION} + \mathbf{X}_i\beta_4 + \varepsilon_p + \varepsilon_i, \quad (4)$$

where PDC_i is the proportion days covered by individual, β_o is the intercept, β_1 is a set of coefficients for each of the job class indicator variables, JOB $CLASS_i$ is an indicator variable classified as manual (blue-collar), nonmanual (white-collar), or not working (retired, disabled, and unemployed) by individual (i), β_2 is the coefficient for the main effect of the intervention, INTERVENTION is the effect of SBI + pillbox, β_3 is the main coefficient of interest for this analysis and represents the moderating effect of job class on the intervention, JOB CLASS*INTERVENTION is the interaction term between each of the job class indicators and

the intervention indicator, X_i represents all other covariates in the model at the individual (*i*) level, β_4 is the set of coefficients for the covariates, ε_p is the model prediction error by pharmacy (*p*) and ε_i is the model prediction error by individual (*i*).

The intervention moderator model demonstrating the intervention's effect on PDC in relation to job strain is shown in equation 5:

$$\mathbf{PDC}_i = \beta_o + \beta_1 \mathbf{JOB\ STRAIN}_i + \beta_2 \mathbf{INTERVENTION} + \beta_3 \mathbf{JOB\ STRAIN*INTERVENTION} + \mathbf{X}_i\beta_4 + \varepsilon_p + \varepsilon_i, \quad (5)$$

where PDC_i is the proportion days covered by individual, β_o is the intercept, β_1 is a set of coefficients for each of the job strain indicator variables, JOB $STRAIN_i$ is an indicator variable classified as active, high strain, low strain, passive, and non-contributing by individual (*i*), β_2 is the coefficient for the main effect of the intervention, INTERVENTION is the effect of SBI + pillbox, β_3 is the main coefficient of interest for this analysis and represents the moderating effect of job strain on the intervention, JOB STRAIN*INTERVENTION is the interaction term between each of the job strain indicators and the intervention indicator, X_i represents all other covariates in the model at the individual (*i*) level, β_4 is the set of coefficients for the covariates, ε_p is the model prediction error by pharmacy (*p*) and ε_i is the model prediction error by individual (*i*).

GLMM allowed for each outcome to be measured independently even though the study involved multiple data sources, data collection methods, and different analysis samples that emerged for any given outcome of interest (e.g. the sample of participants with PDC adherence measures, though overlapping, was distinct from participants with healthcare utilization data).

Covariates across multiple data sets were utilized when available. The GLMM efficiently modeled repeated measures within individual participants and pharmacies for fixed/random effects and clustering (McCulloch & Neuhaus, 2005). Moreover, within the GLMM framework, hypotheses were explored on multiple levels. Pairwise comparisons of job class and job strain utilized a reference category. Post-estimation f-tests were used to compare between job class and job strain that were not specified as the reference category. STATA (version 13, StataCorp, College Station, TX) software was used for the analyses.

4.0 RESULTS

4.1 SAMPLE SELECTION

The occupational health questionnaire was administered to all participants (n=506) with a sample of n=210 completing the questionnaire (response rate of 41.5%). A final sample of n=189 was used for the analysis as pharmacy claims data was provided for these participants. Figure 4 depicts the sample of participants. Non-response to the survey did not appear to vary substantially by store, study treatment group, gender or age.

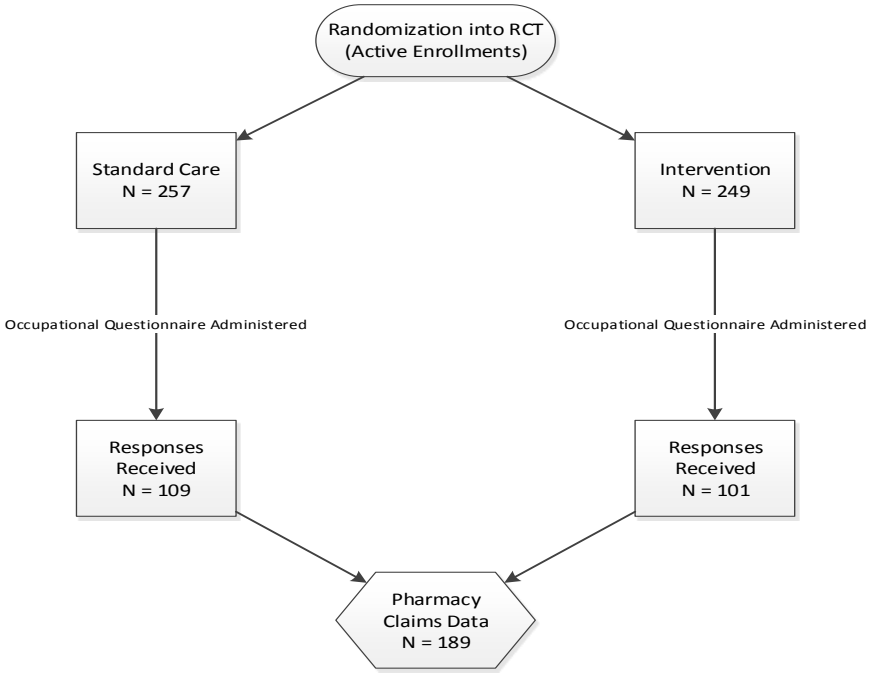

Figure 4. Study Sample

4.2 DESCRIPTIVE STATISTICS

Descriptive statistics of all relevant sample characteristics are tabulated and presented by job strain and job class in Table 3. Continuous covariate outcomes are presented as means and standard errors. Categorical covariates are described as percentages. Covariates that were found to be related to medication adherence are noted within Table 3.

Approximately, half of all individuals were enrolled in the RCT with a primary diagnosis of diabetes. The average participant age was 61 and roughly half of the study population was female. Sixty-one percent were married or had a partner. Less than 20% of the sample failed to complete high school. Thirty-one percent were employed full-time and 59% were retired, disabled, or not employed. Most participants had individual insurance plans (84.4%). Participants had a baseline PDC of 62.8%. Lastly, job class and job strain had equivalent baseline characteristics across a variety of measures of health and health behaviors.

Table 3. Sample Characteristics

		Total Sample	Job Strain					Job Class		
			Active	High Strain	Low Strain	Passive	Non-Contributing	Manual	Nonmanual	Not Working
N		189	64	35	33	42	15	50	120	19
Standard Care (%)			19%	11%	7.4%	12.2%	4%	14%	35%	5%
SBI + pillbox (%)			15%	7.4%	10%	10%	4%	13%	28%	5%
Diabetes Proportion		0.524	0.531	0.514	0.515	0.548	0.467	0.480	0.558	0.421
		(0.036)	(0.063)	(0.086)	(0.088)	(0.078)	(0.133)	(0.071)	(0.046)	(0.116)
PDC		0.628	0.675	0.611	0.735	0.599	0.581	0.666	0.652	0.578
		(0.035)	(0.059)	(0.082)	(0.077)	(0.076)	(0.127)	(0.067)	(0.043)	(0.113)
PDC										
BB	Pre	0.657	0.667	0.659	0.742	0.566	0.646	0.608	0.686	0.662
	Post	(0.038)	(0.066)	(0.088)	(0.057)	(0.09)	(0.18)	(0.061)	(0.05)	(0.153)
CCB	Pre	0.789	0.708	0.859	0.840	0.779	0.897	0.795	0.768	0.897
	Post	(0.031)	(0.064)	(0.052)	(0.057)	(0.072)	(0.084)	(0.051)	(0.044)	(0.071)
Diabetes	Pre	0.657	0.656	0.663	0.719	0.682	0.528	0.754	0.643	0.553
	Post	(0.043)	(0.076)	(0.069)	(0.127)	(0.11)	(0.154)	(0.071)	(0.056)	(0.13)

Table 3 continued

		Total Sample	Job Strain					Job Class		
			Active	High Strain	Low Strain	Passive	Non-Contributing	Manual	Nonmanual	Not Working
RASA	Pre	0.718	0.733	0.573	0.916	0.719	0.701	0.818	0.694	0.652
	Post	(0.04)	(0.058)	(0.109)	(0.031)	(0.12)	(0.121)	(0.06)	(0.054)	(0.127)
Statins	Pre	0.696	0.763	0.639	0.713	0.654	0.609	0.626	0.737	0.606
	Post	(0.029)	(0.042)	(0.072)	(0.06)	(0.076)	(0.109)	(0.064)	(0.034)	(0.097)
PDC80										
BB	Pre	0.560	0.630	0.533	0.500	0.429	0.800	0.385	0.651	0.667
	Post	(0.058)	(0.095)	(0.133)	(0.139)	(0.137)	(0.2)	(0.097)	(0.074)	(0.211)
CCB	Pre	0.727	0.692	0.813	0.714	0.667	0.833	0.704	0.721	0.857
	Post	(0.051)	(0.092)	(0.101)	(0.125)	(0.126)	(0.167)	(0.09)	(0.069)	(0.143)
Diabetes	Pre	0.581	0.727	0.313	0.875	0.556	0.429	0.625	0.595	0.444
	Post	(0.063)	(0.097)	(0.12)	(0.125)	(0.176)	(0.202)	(0.125)	(0.082)	(0.176)
RASA	Pre	0.672	0.593	0.667	0.900	0.750	0.571	0.750	0.650	0.625
	Post	(0.059)	(0.096)	(0.142)	(0.1)	(0.164)	(0.202)	(0.112)	(0.076)	(0.183)
Statins	Pre	0.550	0.615	0.450	0.450	0.652	0.444	0.464	0.597	0.455
	Post	(0.047)	(0.079)	(0.114)	(0.114)	(0.102)	(0.176)	(0.096)	(0.058)	(0.157)
Age		61	61	60	60	59	65	60	60	66
		(0.786)	(1.319)	(1.855)	(1.770)	(1.782)	(2.805)	(1.488)	(0.989)	(2.433)
Female		0.543	0.578	0.853	0.273	0.405	0.667	0.280	0.625	0.722
		(0.036)	(0.062)	(0.062)	(0.079)	(0.077)	(0.126)	(0.064)	(0.044)	(0.109)
Non-white		0.128	0.143	0.143	0.152	0.048	0.200	0.080	0.143	0.158
		(0.024)	(0.044)	(0.060)	(0.063)	(0.033)	(0.107)	(0.039)	(0.032)	(0.086)
Less than High School Degree		0.176	0.048	0.314	0.061	0.214	0.533	0.300	0.076	0.474
		(0.028)	(0.027)	(0.080)	(0.042)	(0.064)	(0.133)	(0.065)	(0.024)	(0.118)
High School Degree		0.277	0.143	0.286	0.364	0.429	0.200	0.500	0.185	0.263
		(0.033)	(0.044)	(0.077)	(0.085)	(0.077)	(0.107)	(0.071)	(0.036)	(0.104)
Four-year Degree		0.282	0.254	0.314	0.333	0.262	0.267	0.120	0.353	0.263
		(0.033)	(0.055)	(0.080)	(0.083)	(0.069)	(0.118)	(0.046)	(0.044)	(0.104)
Professional/Graduate Level Degree		0.266	0.556	0.086	0.242	0.095	0.000	0.080	0.387	0.000
		(0.032)	(0.063)	(0.048)	(0.076)	(0.046)	(0.000)	(0.039)	(0.045)	(0.000)
Married/Partnered		0.612	0.730	0.514	0.636	0.619	0.267	0.560	0.681	0.316
		(0.036)	(0.056)	(0.086)	(0.085)	(0.076)	(0.118)	(0.071)	(0.043)	(0.110)
Independent Living		0.926	0.968	0.943	0.939	0.881	0.800	0.960	0.924	0.842
		(0.019)	(0.022)	(0.040)	(0.042)	(0.051)	(0.107)	(0.028)	(0.024)	(0.086)
Employed Full-time		0.314	0.413	0.171	0.455	0.286	0.000	0.240	0.395	0.000
		(0.034)	(0.063)	(0.065)	(0.088)	(0.071)	(0.000)	(0.061)	(0.045)	(0.000)
Employed Part-time		0.096	0.063	0.086	0.121	0.167	0.000	0.080	0.109	0.053
		(0.022)	(0.031)	(0.048)	(0.058)	(0.058)	(0.000)	(0.039)	(0.029)	(0.053)
Retired		0.356	0.444	0.286	0.333	0.262	0.467	0.340	0.361	0.368
		(0.035)	(0.063)	(0.077)	(0.083)	(0.069)	(0.133)	(0.068)	(0.044)	(0.114)
Disabled		0.170	0.048	0.314	0.061	0.190	0.533	0.260	0.084	0.474

Table 3 continued

	Total Sample	Job Strain					Job Class		
		Active	High Strain	Low Strain	Passive	Non-Contributing	Manual	Nonmanual	Not Working
	(0.027)	(0.027)	(0.080)	(0.042)	(0.061)	(0.133)	(0.063)	(0.026)	(0.118)
Not Employed	0.064	0.032	0.143	0.030	0.095	0.000	0.080	0.050	0.105
	(0.018)	(0.022)	(0.060)	(0.030)	(0.046)	(0.000)	(0.039)	(0.020)	(0.072)
Current Income									
$0 - $15,000	0.240	0.129	0.324	0.133	0.310	0.636	0.271	0.190	0.533
	(0.032)	(0.043)	(0.081)	(0.063)	(0.072)	(0.152)	(0.065)	(0.037)	(0.133)
$15,0001 - $30,000	0.285	0.161	0.382	0.367	0.310	0.364	0.354	0.241	0.400
	(0.034)	(0.047)	(0.085)	(0.089)	(0.072)	(0.152)	(0.070)	(0.040)	(0.131)
$30,001 - $50,000	0.201	0.226	0.147	0.233	0.238	0.000	0.188	0.233	0.000
	(0.030)	(0.054)	(0.062)	(0.079)	(0.067)	(0.000)	(0.057)	(0.039)	(0.000)
$50,001 - $75,000	0.145	0.210	0.147	0.200	0.048	0.000	0.167	0.147	0.067
	(0.026)	(0.052)	(0.062)	(0.074)	(0.033)	(0.000)	(0.054)	(0.033)	(0.067)
$75,001 - $100,000	0.067	0.129	0.000	0.067	0.048	0.000	0.000	0.103	0.000
	(0.019)	(0.043)	(0.000)	(0.046)	(0.033)	(0.000)	(0.000)	(0.028)	(0.000)
>$100,000	0.061	0.145	0.000	0.000	0.048	0.000	0.021	0.086	0.000
	(0.018)	(0.045)	(0.000)	(0.000)	(0.033)	(0.000)	(0.021)	(0.026)	(0.000)
Prior Income									
$0 - $15,000	0.217	0.119	0.286	0.150	0.304	0.429	0.250	0.167	0.500
	(0.038)	(0.051)	(0.087)	(0.082)	(0.098)	(0.202)	(0.078)	(0.042)	(0.167)
$15,0001 - $30,000	0.192	0.071	0.321	0.200	0.174	0.429	0.219	0.167	0.300
	(0.036)	(0.040)	(0.090)	(0.092)	(0.081)	(0.202)	(0.074)	(0.042)	(0.153)
$30,001 - $50,000	0.200	0.190	0.107	0.300	0.261	0.143	0.188	0.218	0.100
	(0.037)	(0.061)	(0.060)	(0.105)	(0.094)	(0.143)	(0.070)	(0.047)	(0.100)
$50,001 - $75,000	0.208	0.167	0.214	0.300	0.261	0.000	0.281	0.205	0.000
	(0.037)	(0.058)	(0.079)	(0.105)	(0.094)	(0.000)	(0.081)	(0.046)	(0.000)
$75,001 - $100,000	0.058	0.143	0.036	0.000	0.000	0.000	0.000	0.090	0.000
	(0.021)	(0.055)	(0.036)	(0.000)	(0.000)	(0.000)	(0.000)	(0.033)	(0.000)
>$100,000	0.125	0.310	0.036	0.050	0.000	0.000	0.063	0.154	0.100
	(0.030)	(0.072)	(0.036)	(0.050)	(0.000)	(0.000)	(0.043)	(0.041)	(0.100)
Individual Plan	0.840	0.859	0.853	0.818	0.810	0.867	0.840	0.833	0.889
	(0.027)	(0.044)	(0.062)	(0.068)	(0.061)	(0.091)	(0.052)	(0.034)	(0.076)
Group Plan	0.074	0.109	0.088	0.061	0.048	0.000	0.040	0.100	0.000
	(0.019)	(0.039)	(0.049)	(0.042)	(0.033)	(0.000)	(0.028)	(0.028)	(0.000)
Military/Government	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Medicaid	0.005	0.000	0.000	0.000	0.024	0.000	0.020	0.000	0.000
	(0.005)	(0.000)	(0.000)	(0.000)	(0.024)	(0.000)	(0.020)	(0.000)	(0.000)
Medicare	0.064	0.016	0.029	0.091	0.119	0.133	0.100	0.042	0.111
	(0.018)	(0.016)	(0.029)	(0.051)	(0.051)	(0.091)	(0.043)	(0.018)	(0.076)
Not Insured	0.016	0.016	0.029	0.030	0.000	0.000	0.000	0.025	0.000

Table 3 continued

	Total Sample	Job Strain					Job Class		
		Active	High Strain	Low Strain	Passive	Non-Contributing	Manual	Nonmanual	Not Working
	(0.009)	(0.016)	(0.029)	(0.030)	(0.000)	(0.000)	(0.000)	(0.014)	(0.000)
DX Diabetes	0.633	0.641	0.588	0.636	0.619	0.733	0.600	0.650	0.611
	(0.035)	(0.060)	(0.086)	(0.085)	(0.076)	(0.118)	(0.070)	(0.044)	(0.118)
DX Cholesterol	0.888	0.875	0.853	0.970	0.857	0.933	0.880	0.883	0.944
	(0.023)	(0.042)	(0.062)	(0.030)	(0.055)	(0.067)	(0.046)	(0.029)	(0.056)
DX Heart Disease	0.266	0.281	0.265	0.152	0.310	0.333	0.320	0.242	0.278
	(0.032)	(0.057)	(0.077)	(0.063)	(0.072)	(0.126)	(0.067)	(0.039)	(0.109)
DX Hypertension	0.771	0.750	0.824	0.727	0.762	0.867	0.840	0.733	0.833
	(0.031)	(0.055)	(0.066)	(0.079)	(0.067)	(0.091)	(0.052)	(0.041)	(0.090)
DX Stroke	0.080	0.094	0.088	0.030	0.095	0.067	0.100	0.075	0.056
	(0.020)	(0.037)	(0.049)	(0.030)	(0.046)	(0.067)	(0.043)	(0.024)	(0.056)
DX Depression	0.266	0.250	0.235	0.182	0.333	0.400	0.200	0.283	0.333
	(0.032)	(0.055)	(0.074)	(0.068)	(0.074)	(0.131)	(0.057)	(0.041)	(0.114)
DX Other Chronic Disease	0.410	0.375	0.471	0.455	0.429	0.267	0.340	0.458	0.278
	(0.036)	(0.061)	(0.087)	(0.088)	(0.077)	(0.118)	(0.068)	(0.046)	(0.109)
How Often Prepare List of Questions for MD (1-6)	3.250	3.266	2.794	3.182	3.524	3.600	2.800	3.350	3.833
	(0.120)	(0.208)	(0.242)	(0.293)	(0.260)	(0.456)	(0.221)	(0.149)	(0.406)
How Often Ask MD to Understand Treatment (1-6)	4.293	4.484	4.206	4.121	4.333	3.933	3.880	4.492	4.111
	(0.119)	(0.199)	(0.283)	(0.298)	(0.254)	(0.408)	(0.230)	(0.147)	(0.378)
How Often Discuss Personal Problems with MD Related to Illness (1-6)	3.489	3.563	3.882	3.000	3.405	3.600	3.160	3.575	3.833
	(0.127)	(0.224)	(0.289)	(0.320)	(0.273)	(0.335)	(0.227)	(0.167)	(0.336)
Health (1-5; Lower is Better)	3.080	2.969	3.029	2.939	3.310	3.333	3.360	2.950	3.167
	(0.068)	(0.126)	(0.166)	(0.123)	(0.134)	(0.270)	(0.124)	(0.084)	(0.246)
Robust standard errors in parentheses									

Correlations between the study variables, specifically job strain and PDC for diabetes and statins are shown in Table 4. Correlation coefficients show that females are less likely to have a low strain job. Active strain is positively correlated with income and education. Individuals in high strain jobs have low adherence to statins. Lastly, statin adherence is positively correlated with adherence to diabetes medications.

Table 4. Correlations between the Study Variables

						Job Strain					PDC	
		Female	Education	Current Income	Previous Income	Active	High Strain	Low Strain	Passive	Non-Contributing	Diabetes	Statins
Female		1										
Education		-0.04	1									
Current Income		-0.10	0.47*	1								
Previous Income		-0.12	0.30*	0.30*	1							
Job Strain	Active	0.05	0.46*	0.39*	0.31*	1						
	High Strain	0.29*	-0.21*	-0.17*	-0.03	-0.34*	1					
	Low Strain	-0.25*	0.05	-0.04	-0.05	-0.33*	-0.22*	1				
	Passive	-0.15*	-0.20*	-0.08	-0.17*	-0.38*	-0.25*	-0.25*	1			
	Non-Contributing	0.07	-0.25*	-0.26*	-0.17*	-0.21*	-0.14	-0.14	-0.16*	1		
PDC	Diabetes	-0.01	0.12	0.05	0.09	0.16	-0.09	0.03	-0.07	-0.08	1	
	Statins	-0.12	-0.07	0.06	0.10	0.10	-0.18*	0.07	-0.02	0.02	0.49*	1
*p<0.05												

4.3 PRE-INTERVENTION MODELS

The pre-intervention models depicting PDC at baseline for job class and job strain are presented by medication class.

4.3.1 Pre-Intervention Models for Job Class

Table 5 shows baseline PDC as a function of job class with the manual job class as the reference category. The results show significance, although minimal, on adherence for both nonmanual workers taking BBs (0.168; p=0.096) and participants prescribed CCBs who are not working (-0.307; p=0.096) as compared to the manual job class. Figure 5 illustrates baseline PDC as a function of job class with the manual job class as the reference category as presented in Table 5.

Table 5. Baseline PDC as a Function of Job Class

Reference Category: Manual		Baseline Proportion Days Covered (PDC) by Medication Class					
		Beta Blockers (BB)	Calcium Channel Blockers (CCB)	Diabetes	Renin Angiotensin System Antagonists (RASA)	Statins	Combined PDC across All Medication Classes
N		80	68	114	121	163	187
Job Class	Nonmanual	0.168*	-0.152	0.107	0.028	-0.038	0.011
		(0.01)	(0.13)	(0.09)	(0.09)	(0.08)	(0.060)
	Not Working	-0.11	-0.307*	-0.076	-0.192	-0.118	-0.098
		(0.156)	(0.181)	(0.127)	(0.124)	(0.111)	(0.086)
Robust standard errors in parentheses *p<0.1							
Other covariates not presented here are Age, Female, Nonwhite, Married/Partnered, Diabetes Diagnosis, Cholesterol Diagnosis, Heart Disease Diagnosis, Hypertension Diagnosis, Stroke Diagnosis, Depression Diagnosis, Other Diagnosis, Full-time Employment, Part-time Employment, Retired, Disabled, Not Employed, Current Income & Prior Income.							

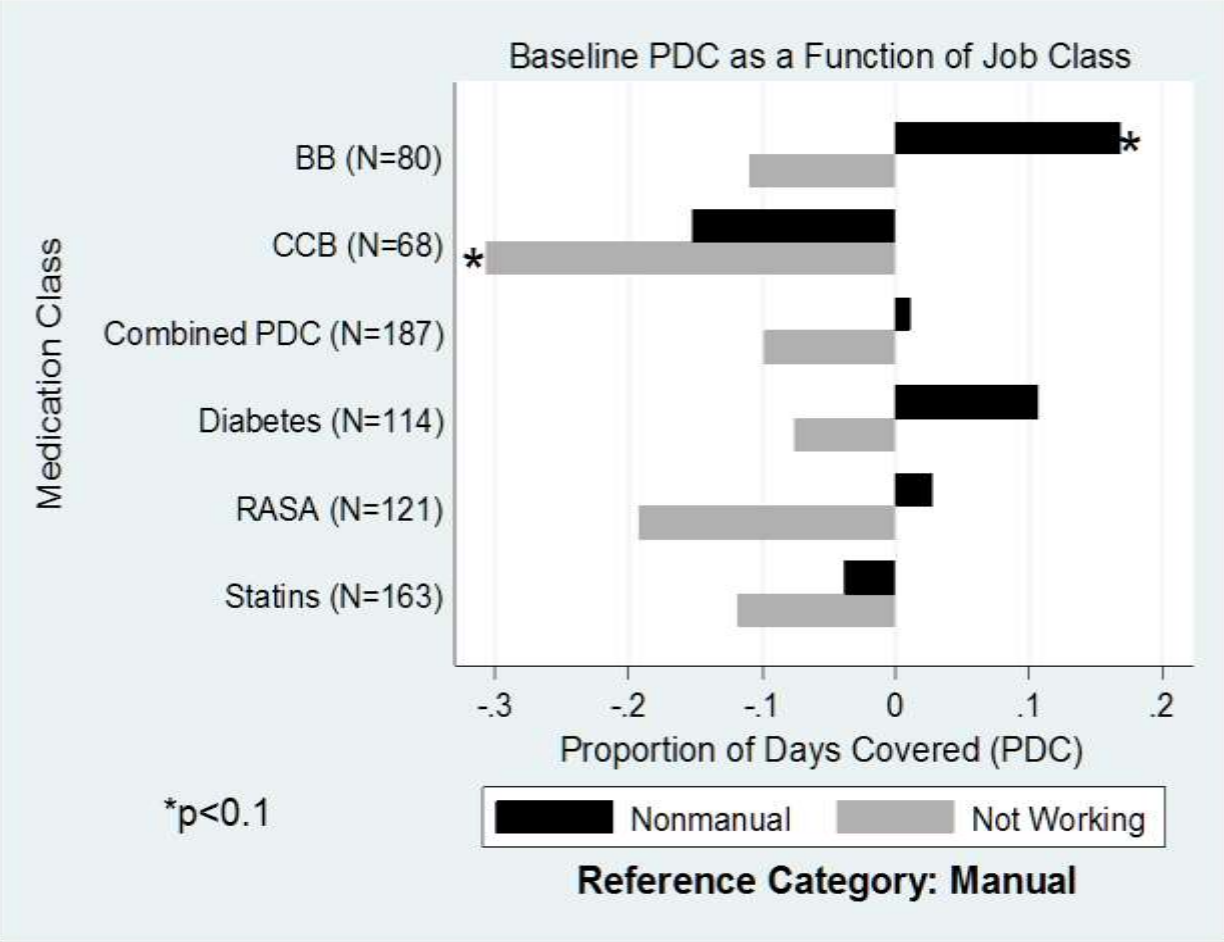

Figure 5. Baseline PDC as a Function of Job Class

4.3.2 Pre-Intervention Models for Job Strain

Table 6 presents baseline PDC as a function of job strain with the reference category as the active strain. The results demonstrate that the non-contributing group has lower adherence measured by PDC than the active strain across all medication classes. In all models post estimation calculations were made to compare coefficients to one and other. Comparing across job strain coefficients for the medication class RASA, the low strain (0.174) job type had a higher PDC than the non-contributing group (-0.264; p=0.004). Participants prescribed RASA

also showed that the passive strain (-0.082) had a lower PDC than participants with a low strain (0.174; p=0.017) job type. High strain participants (-0.143) had a significantly lower PDC than participants with a low strain (0.053; p=0.053) job type for the statin medication class. Figure 6 illustrates baseline PDC as a function of job strain with the active job strain as the reference category as presented in Table 6. The results suggest that job strain is strongly associated with medication adherence.

Table 6. Baseline PDC as a Function of Job Strain

Reference Category: Active Strain		Baseline Proportion Days Covered (PDC) by Medication Class					
		Beta Blockers (BB)	Calcium Channel Blockers (CCB)	Diabetes	Renin Angiotensin System Antagonists (RASA)	Statins	Combined PDC across All Medication Classes
N		80	68	114	121	163	187
Job Strain	High Strain	0.036	-0.033	-0.086	0.049	-0.143*	-0.099
		(-0.132)	(0.159)	(0.106)	(0.107)	(0.089)	(0.071)
	Low Strain	0.083	-0.007	-0.04	0.174*	0.053*	0.052
		(0.136)	(0.173)	(0.108)	(0.104)	(0.09)	(0.071)
	Passive	-0.094	0.024	-0.103	-0.082	-0.041	-0.049
		(0.131)	(0.177)	(0.096)	(0.097)	(0.085)	(0.068)
	Non-Contributing	-0.145	-0.156	-0.228*	-0.264***	-0.096	-0.119
		(0.194)	(0.197)	(0.141)	(0.144)	(0.126)	(0.097)
Robust standard errors in parentheses ***p<0.01, *p<0.1							
Other covariates not presented here are Age, Female, Nonwhite, Married/Partnered, Diabetes Diagnosis, Cholesterol Diagnosis, Heart Disease Diagnosis, Hypertension Diagnosis, Stroke Diagnosis, Depression Diagnosis, Other Diagnosis, Full-time Employment, Part-time Employment, Retired, Disabled, Not Employed, Current Income & Prior Income.							

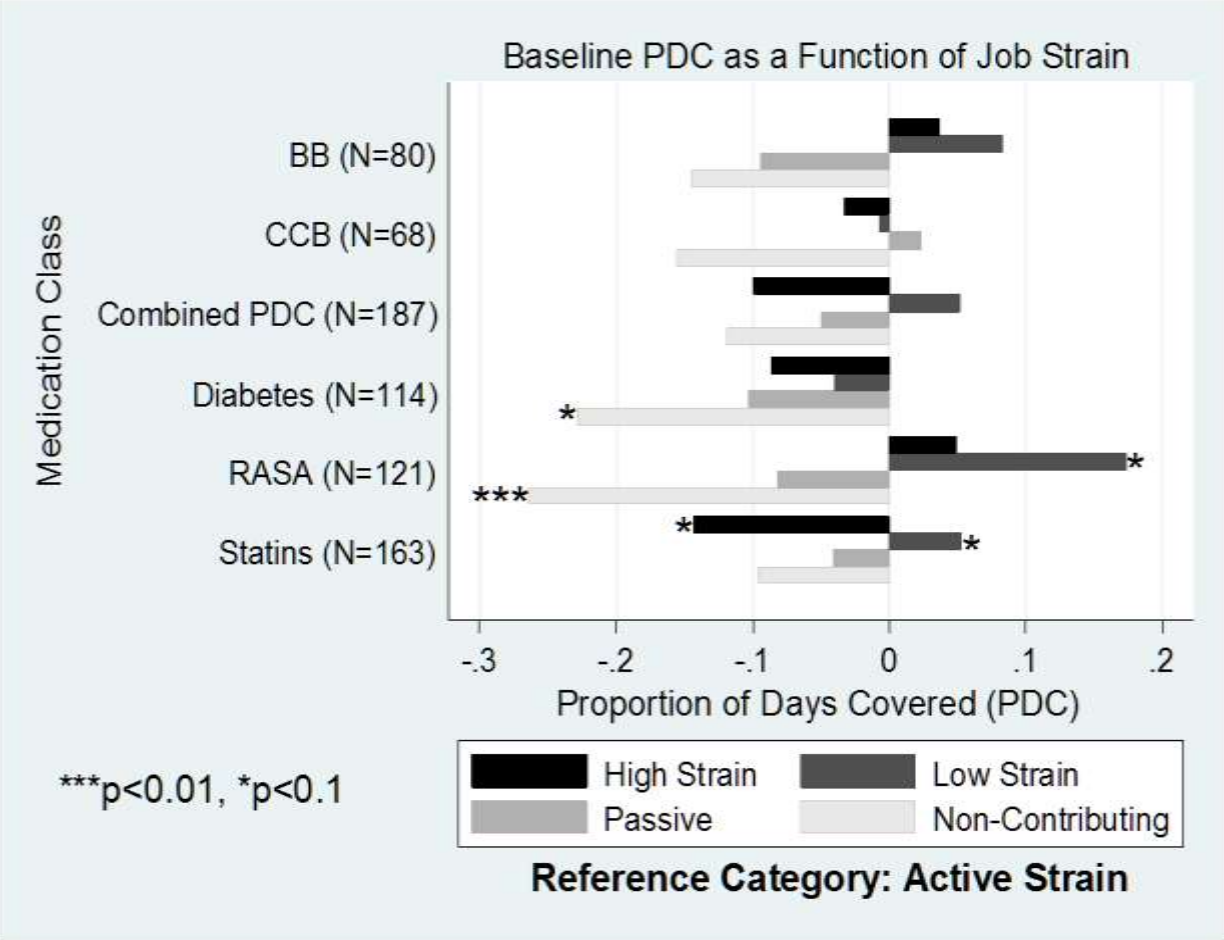

Figure 6. Baseline PDC as a Function of Job Strain

4.4 INTERVENTION MODERATOR MODELS

The intervention moderator models are used to estimate how job class and job strain influence the intervention's effect on PDC. The intervention moderator tables present the results of five models that show different specifications for covariates as more control variables are

included. The models are noted in each subsequent table with Model 5 being the most robust specification (i.e. containing all covariates).

4.4.1 Intervention Moderator Models for Job Class

Table 7 shows that job class does not have an impact on the intervention. Negative effects are consistently seen in all models relative to the manual job class (reference category). Figure 7 illustrates the moderating effect of job class on the impact of the intervention with the manual job class as the reference category as presented in Table 7.

Table 7. Moderating Effects of Job Class on Impact of Intervention

Reference Category: Manual		Adjusted Δ in Proportion Days Covered (PDC)				
		Model 1	Model 2	Model 3	Model 4	Model 5
Job Class	Nonmanual	-0.123	-0.135	-0.111	-0.081	-0.072
		(0.083)	(0.084)	(0.085)	(0.084)	(0.087)
	Not Working	-0.12	-0.124	-0.118	-0.16	-0.189
		(0.146)	(0.146)	(0.147)	(0.152)	(0.157)
Robust standard errors in parentheses						
Model 1: Study Group, Job Strain, Baseline PDC; **Model 2**: Model 1 + Age, Female, Nonwhite, Married/Partnered; **Model 3**: Model 2 + High School Degree, Four-year Degree, Professional/Graduate Level Degree, Part-Time Employment, Retired, Disabled, Unemployment, Current and Prior Income, Diabetes Diagnosis, Cholesterol Diagnosis, Heart Disease Diagnosis, Hypertension Diagnosis, Stroke Diagnosis, Depression Diagnosis, Other Diagnosis; **Model 4**: Model 3 + Group Insurance, Military/Government Insurance, Medicaid Insurance, Health (1-5; Lower is Better), Health limited physical activities (1-5; Lower is Better), Bothered by emotional problems (1-5; Lower is Better), Limited work in and out of home (1-5; Lower is Better), Interfered with normal social activities (1-5; Lower is Better); **Model 5**: Model 4 + How Often Prepare List of Questions for MD (1-6), How Often Ask MD to Understand Treatment (1-6), How Often Discuss Personal Problems with MD Related to Illness (1-6).						

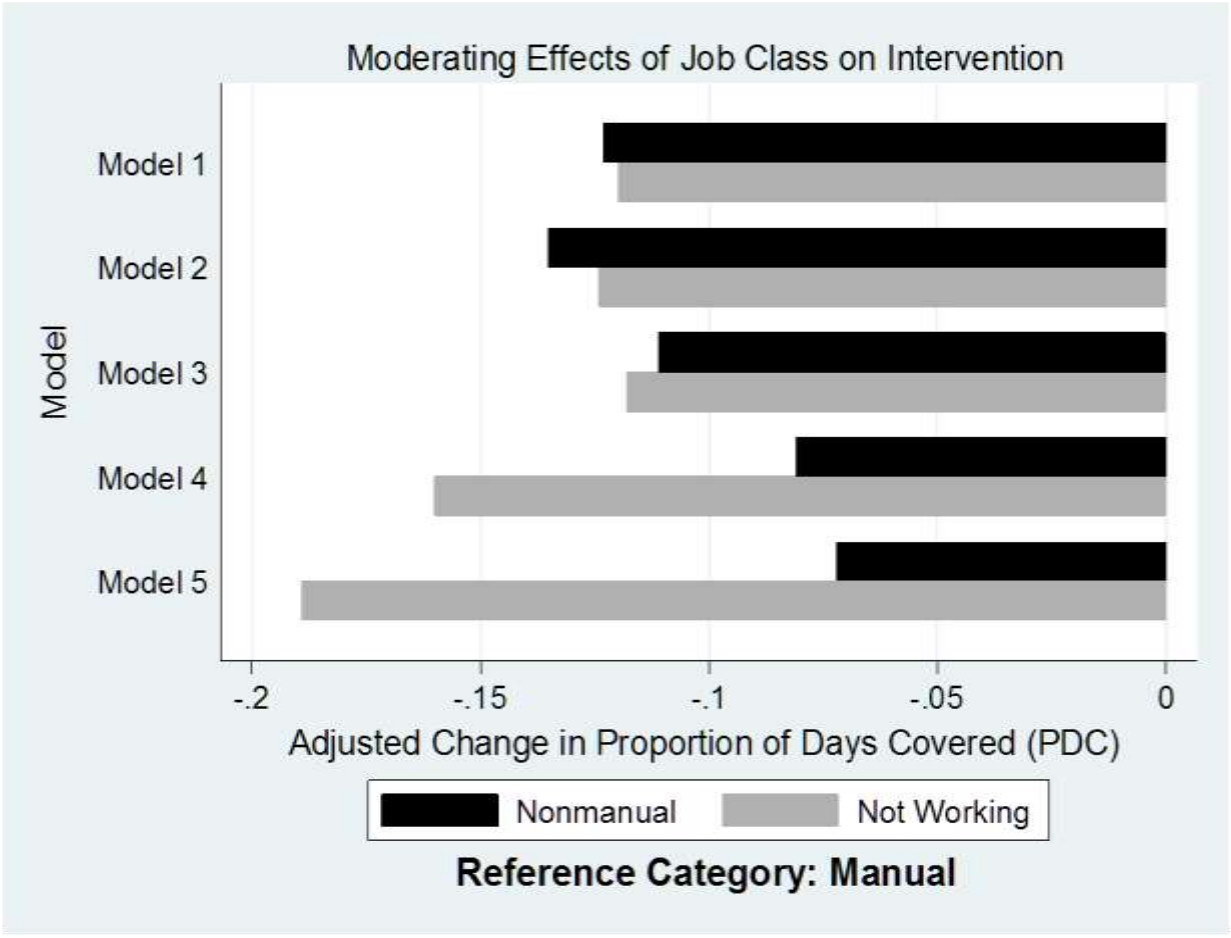

Figure 7. Moderating Effects of Job Class on Impact of Intervention

4.4.2 Intervention Moderator Models for Job Strain

Changes in PDC in response to the intervention are positively moderated by all job strains, except non-contributing, relative to the active strain as shown in Table 8. The low strain job type has the largest moderating effect of the intervention ($p<0.01$) with an effect estimate range from 0.169 ($p<0.01$) to 0.202 ($p<0.01$). Additionally, the moderating effect for the high strain job type in Model 4 is positive and significant (0.172; $p<0.1$). Model five, the most robust specification, yields a 0.181 adjusted change in PDC or 18.1 percentage point increase in PDC

for the low strain job type. Figure 8 illustrates the moderating effect of job strain on the impact of the intervention with the active job strain as the reference category as presented in Table 8. The results of the intervention moderator models demonstrate that job strain is associated with the impact of the intervention.

Table 8. Moderating Effects of Job Strain on Impact of Intervention

Reference Category: Active Strain		Adjusted Δ in Proportion Days Covered (PDC)				
		Model 1	Model 2	Model 3	Model 4	Model 5
Job Strain	High Strain	0.114	0.111	0.125	0.172*	0.141
		(0.082)	(0.087)	(0.093)	(0.096)	(0.097)
	Low Strain	0.179***	0.169***	0.202***	0.178***	0.181***
		(0.062)	(0.06)	(0.052)	(0.054)	(0.051)
	Passive	0.144	0.146	0.134	0.135	0.147
		(0.108)	(0.109)	(0.111)	(0.098)	(0.101)
	Non-Contributing	0.063	0.075	0.059	-0.028	-0.021
		(0.154)	(0.152)	(0.156)	(0.193)	(0.191)

Robust standard errors in parentheses
***p<0.01, *p<0.1

Model 1: Study Group, Job Strain, Baseline PDC;
Model 2: Model 1 + Age, Female, Nonwhite, Married/Partnered;
Model 3: Model 2 + High School Degree, Four-year Degree, Professional/Graduate Level Degree, Part-Time Employment, Retired, Disabled, Unemployment, Current and Prior Income, Diabetes Diagnosis, Cholesterol Diagnosis, Heart Disease Diagnosis, Hypertension Diagnosis, Stroke Diagnosis, Depression Diagnosis, Other Diagnosis;
Model 4: Model 3 + Group Insurance, Military/Government Insurance, Medicaid Insurance, Health (1-5; Lower is Better), Health limited physical activities (1-5; Lower is Better), Bothered by emotional problems (1-5; Lower is Better), Limited work in and out of home (1-5; Lower is Better), Interfered with normal social activities (1-5; Lower is Better);
Model 5: Model 4 + How Often Prepare List of Questions for MD (1-6), How Often Ask MD to Understand Treatment (1-6), How Often Discuss Personal Problems with MD Related to Illness (1-6).

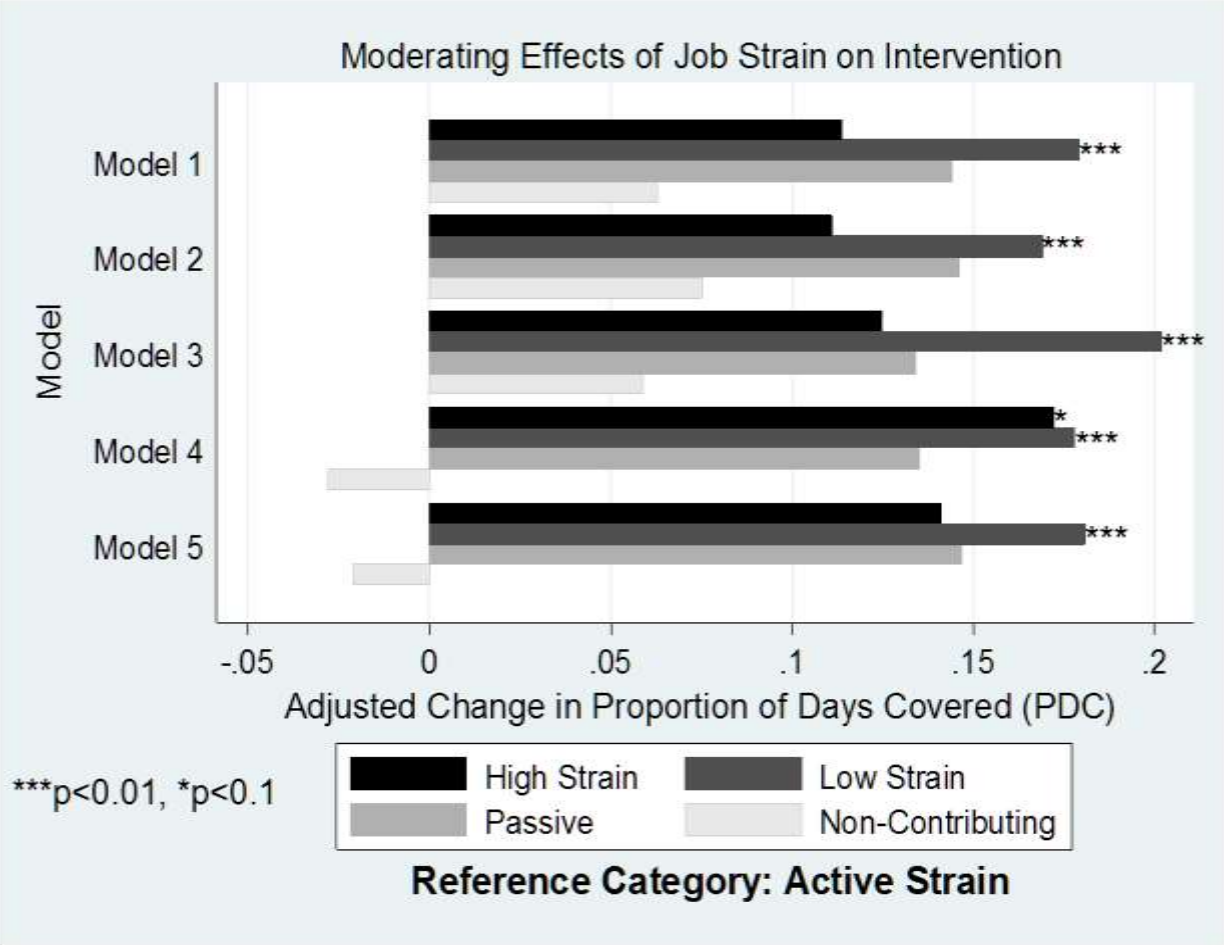

Figure 8. Moderating Effects of Job Strain on Impact of Intervention

5.0 DISCUSSION

Table 9 summarizes the main findings of this research study and these findings are presented in the subsequent sections of this discussion section.

Table 9. Main Findings

Pre-Intervention Models		Intervention Moderator Models	
Job Class	Job Strain	Job Class	Job Strain
• Minimal significance on adherence improvement for nonmanual workers taking BBs (0.168; p<0.1) • Minimal significance on adherence improvement for participants not working and prescribed CCBs (-0.307; p<0.1)	• Non-contributing group has lower adherence measured by PDC than the active strain across all medication classes • Comparing across job strain coefficients for the medication class RASA, the low strain (0.174) job type had a higher PDC than the passive (-0.082) job type followed by the non-contributing group (-0.264; p=0.004) • High strain (-0.143) job type had a significantly lower PDC than the low strain job type (0.053; p=0.053) for the statin medication class	• Job class does not have an impact on the intervention	• Low strain has the largest moderating effect of the intervention with an effect estimate range from 0.169 to 0.202 (p<0.01) • Model five, the most robust specification, yields an 18.1 percentage point increase in PDC for low strain (p<0.01) • Moderating effect for high strain in Model 4 is positive and significant (0.172; p<0.1)

5.1 PRE-INTERVENTION MODELS

The pre-intervention models of the association of PDC at baseline revealed that job strain is correlated with medication adherence, while job class, classically defined as manual (blue-collar), nonmanual (white-collar), and not working (retired, disabled, and unemployed), does not have a strong association with medication adherence. Comparing across post-hoc testing for job strain in the RASA and statin medication classes, the low strain job type has a more positive association with PDC then both the high strain job type and passive job type, followed by the non-contributing group.

Based on other literature, individuals in the high strain classification have the poorest health, where demands are high, but the employee's ability to use skill or authority to address these demands are low (Amick III et al., 1998; de Jonge, Dollard, Dormann, Le Blanc, & Houtman, 2000; Lerner et al., 1994; Lewchuk, Clarke, & De Wolff, 2008; Stansfeld & Candy, 2006; Theorell et al., 1988; Vermeulen & Mustard, 2000). The results of the present study are consistent with this literature and add to it by providing evidence that health behaviors, in this case medication adherence, may be a key factor in deteriorating health.

The results imply several possible hypotheses. Individuals in a high strain job type have very little autonomy and so perhaps over time they are being conditioned to be passive participants in their health. If such a hypothesis were true, then providing an intervention tailored to high strain occupations may help people manage their health behaviors, specifically improving their adherence to a prescribed medication regimen. Such hypotheses also recommend innovative strategies to be explored. For example, an employer might offer rotations through different job activities in an effort to foster job autonomy. However, it must be noted

that hypotheses based on these results alone face a major challenge from selection bias. Given that the results are cross-sectional, it cannot be ruled out that unobserved individual characteristics resulting from an individual's life experiences may lead to both high strain occupations and lower adherence. Such a scenario reduces the impact of the intervention described above. Regardless of selection bias, though, the finding of high strain occupations as a risk factor for low adherence still remains viable.

Individuals of the non-contributing group are people who, even after controlling for education and income, have potential unobserved characteristic(s) that lead to poor adherence and not being active members of the labor market. In terms of public health significance, a lack of job status or a certain type of job status could be a key indicator for developing an alternative intervention.

An alternative to this logic may be that job stress or job strain leads to low medication adherence. For example, an individual in the non-contributing group (retired, disabled, or not working) may have stress in their daily life, which causes extreme anxiety. This anxiety may lead to the individual not working and consequently, an inability to obtain their prescribed medication regimen. Perhaps the non-contributing group produces stress factors that are not explicit, however these factors fit the model, indicating that stress is a predictor of low medication adherence. Additional analyses can attempt to discern whether it is the unobserved part of an individual or the lack of engagement in the labor market that causes low medication adherence. The latter may be ameliorated by interventions focusing on physical and psychological stressors.

The positive association with adherence for low strain job types (low psychological demand, high decision latitude) seems to allow participants with this job strain the capability to

modify their health behavior. Traditionally, low strain occupations have been characterized as "healthier" job types (Lerner et al., 1994). Characterized by the *Occupational Distribution of Psychosocial Job Characteristics*, examples of low strain job types are a dentist, lineman, natural scientist, and architect (Appendix C). In addition to low psychological demand and high decision latitude or high job control, low strain occupations may provide a fairly secure work schedule, decreased physical stress, and decreased psychological stress.

In summary, job class is not correlated with medication adherence. However, job strain is constructed in a manner that more accurately correlates occupation with medication adherence. Individuals with a low strain job type adhere to their medication regimen, while the high strain, passive, and non-contributing groups are most at risk for poor medication adherence. Further analysis of these job types with respect to tailored interventions may reveal ways to improve medication adherence and other health behaviors.

5.2 INTERVENTION MODERATOR MODELS

The intervention moderator models demonstrate how job class and job strain influence the intervention effect (SBI + pillbox) on PDC. Model estimates show that job class does not have an effect on the intervention. However, job strain influences the intervention effect on PDC and the effect is different across job strains.

The low strain job type demonstrates a substantially high response on the intervention effect across all models. Model five, the most robust specification, yields a 0.181 adjusted change in PDC or 18.1 percentage point increase in PDC. This increase reveals a strong association between job strain and medication adherence. It can be interpreted that individuals in

low strain occupations have the ability to process information as a result of an intervention and positively adhere to health behaviors that promote their wellness.

High strain job types demonstrate a significant effect on the intervention in Model 4, which includes specifications on insurance and other health behaviors. In this instance, high strain job types are similar to low strain job types in health behaviors with respect to the following: health limited physical activities, bothered by emotional problems, limited work in and out of home, interfered with normal social activities.

One of the challenges in examining medication adherence is that a ceiling effect exists. That is if an individual has 0.9 PDC, they can only improve 10 percentage points or by 0.1 PDC. Whereas if someone has 0.3 PDC, they can undergo a greater improvement of 0.7 PDC. The results presented in Table 8 indicate that the high strain job type has overall low adherence, and therefore can undergo a large improvement in their adherence with respect to the intervention. The low strain job type exhibited high PDC, yet the low strain job type improved by 0.18 PDC. This strengthens the interpretation that low job strain indeed produces a moderating effect and the effect is not an artifact of the mathematics in determining PDC.

6.0 SUMMARY

The objective of this dissertation was to examine the relationship between occupational factors and health behaviors. The primary new finding is job strain is correlated with medication adherence. A positive association exists between adherence and low strain job types, which offer low psychological demand with high decision latitude or high job control and provide a fairly stable work schedule, decreased physical stress, and decreased psychological stress. Several possible hypotheses implied by these results are that such occupational conditions reinforce job autonomy in participants and allow the mental aptitude needed to modify their health behaviors. Therefore, a stable psychological well-being may lead to the promotion of an individual's self-efficacy in performing positive health behaviors (i.e. medication adherence).

6.1 LIMITATIONS

A challenge to such hypotheses is selection bias. Individuals with certain characteristics (e.g. high self-efficacy) may simply choose both low-strain occupations and have a propensity for high adherence. The second part of this study avoids some of the challenge of selection bias since it looked at participants over time and in conjunction with an intervention. Both the pre-intervention models and intervention moderator models reveal that job class is not correlated

with medication adherence. However, the pre-intervention models and intervention moderator models demonstrate a strong association between job strain and medication adherence.

Additionally, sample selection was also a limitation in the study design. The RCT provided a convenient sample of individuals presenting with certain criteria at community pharmacies. Among those who received the occupational health questionnaire, approximately 50% of the sample responded and had other data sources available to be matched to them, respectively. The sample responding to the questionnaire did not differ from the RCT sample by age, gender, pharmacy, or study treatment groups. However, it is likely that unobserved characteristics exist for participants who responded to the questionnaire versus those who did not. For example, participants that responded might be healthier, more educated and higher functioning. Overall, this represents a threat to the external validity of the study results. Nonetheless, this is a prospective research study that has utilized a unique and difficult to obtain data set, describing characteristics about job type and health behaviors such as adherence. This study sample brings to light new information on the relationship between occupational history and medication adherence. Ideally, future work should be continued to build on the results of this study by assessing more representative samples to corroborate and expand this new knowledge.

6.2 STRENGTHS

This study also had several important strengths in its design. First, this is an innovative study that analyzes job class and job strain and its effect on medication adherence.

Administrative insurance claims data were used, which is considered an established approach in assessing medication adherence.

Additionally, GLMM was used to efficiently model repeated measures within individual participants and clustering within pharmacies. This statistical framework was able to successfully handle any abnormalities in the distribution of the dependent variable (PDC). Ultimately, treating the dependent variable as linear or continuous was the best fit for the distribution of the data.

Lastly, a well-established model was utilized in discerning job strain for various self-reported job types. The Karasek demand-control model is a widely accepted model used to measure the psychological demands of a job and the worker's ability to use skills or authority to address those demands (i.e. decision latitude). The model has been found to predict several adverse health outcomes, specifically CVD.

6.3 NEXT STEPS

The results of this study reveal that job strain should be considered in strategizing occupation-specific interventions for improving medication adherence. By examining an established and widely accepted model in characterizing job strain, employers can utilize this methodology in assessing their own workplace population. This information can then be used to develop occupation-specific interventions using passive (e.g. pillbox) and active approaches (e.g. SBI, interactive module, web-based application) for implementation into a disease management component of a workplace wellness program. A return on investment analysis can then be conducted to assess healthcare costs. Development of occupation-specific interventions

designed to improve medication adherence in individuals with chronic disease can contribute to a new body of knowledge aimed at reducing healthcare costs.

Additionally, the results of this study recommend new areas of targeted research on interventions and health behaviors. Future studies should aim to evaluate data on health behaviors. For example, based on job type, to what extent does an individual's involvement in their healthcare (e.g. how often an individual prepares a list of questions for the physician) influence their ability to successfully perform health behaviors (e.g. medication adherence) to reach a desired health outcome. This information would serve to enhance the relationship between occupational factors and medication adherence.

APPENDIX A: OCCUPATIONAL HEALTH QUESTIONNAIRE

Dear Participant,

We appreciate your participation in the Eco-Phil study. The purpose of this mailing is to request that you provide answers to additional questions that will help to determine if occupational history effects the ability to take medication.

Your voluntary completion of these questions and subsequent mailing back to the University of Pittsburgh indicates your agreement to provide this information. This information is very important to the results of the study. Your responses will only be linked to the code number on this letter, so in order to protect your privacy, please do not put your name on this letter. A return postage-stamped envelope is provided to further secure your privacy.

1. What is your Job Title (Occupation) OR if not working, what was your most recent Job Title?

   _____

2. What is your Job setting (work location) OR if not working, what was your most recent setting?

   _____

3. What is your current approximate gross annual household income AND your prior annual household income if unemployed, disabled, or retired)? Please include ALL household members and ALL income sources (wages, child support, alimony, income from assets, disability, unemployment compensation, public assistance, and pensions, social security and other retirement income).

CURRENT INCOME

O $0 – 15,000
O $15,001 - $30,000
O $30,001 - $50,000
O $50,001 - $75,000
O $75,001 - $100,000
O more than $100,000

PRIOR INCOME
(if unemployed, disabled, or retired)

O $0 – 15,000
O $15,001 - $30,000
O $30,001 - $50,000
O $50,001 - $75,000
O $75,001 - $100,000
O more than $100,000
O Not Applicable

APPENDIX B: INSTITUTIONAL REVIEW BOARD APPROVAL

University of Pittsburgh
Institutional Review Board

3500 Fifth Avenue
Ground Level
Pittsburgh, PA 15213
(412) 383-1480
(412) 383-1508 (fax)
http://www.irb.pitt.edu

Memorandum

To: Janice Pringle

From: Christopher Ryan Vice Chair

Date: 10/2/2013

IRB#: MOD12050040-03 / PRO12050040

Subject: Prospective Study on a Pharmacist-led Intervention to Improve Medication Adherence

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The University of Pittsburgh Institutional Review Board reviewed and approved the requested modifications by expedited review procedure authorized under 45 CFR 46.110 and 21 CFR 56.110.

The IRB has approved the waiver for the requirement to obtain a written informed consent.

Modification Approval Date: 10/2/2013
Expiration Date: 4/1/2014

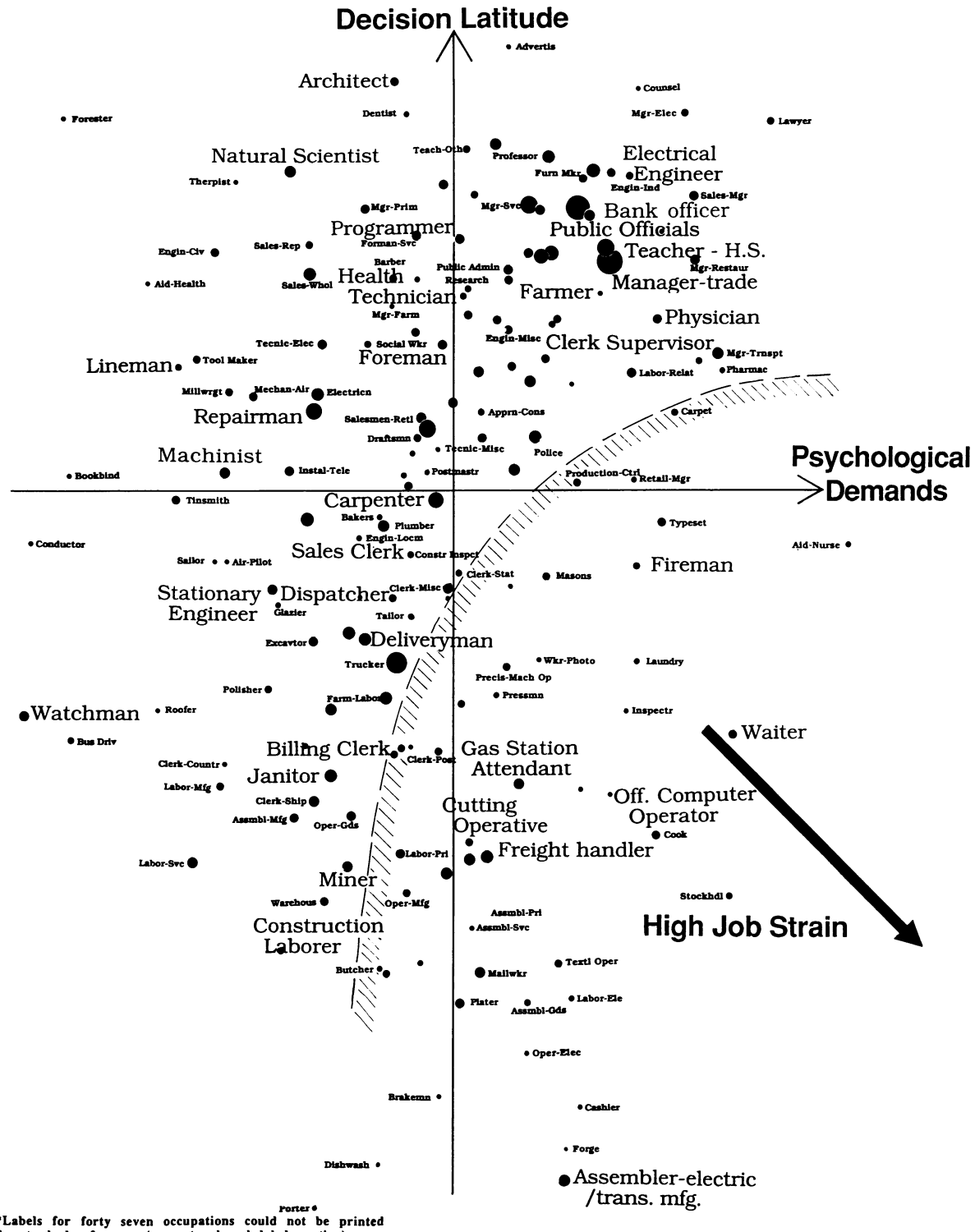
For studies being conducted in UPMC facilities, no clinical activities that are impacted by the modifications can be undertaken by investigators until they have received approval from the UPMC Fiscal Review Office.

Please note that it is the investigator's responsibility to report to the IRB any unanticipated problems involving risks to subjects or others [see 45 CFR 46.103(b)(5) and 21 CFR 56.108(b)]. Refer to the IRB Policy and Procedure Manual regarding the reporting requirements for unanticipated problems which include, but are not limited to, adverse events. If you have any questions about this process, please contact the Adverse Events Coordinator at 412-383-1480.

The protocol and consent forms, along with a brief progress report must be resubmitted at least one month prior to the renewal date noted above as required by FWA00006790 (University of Pittsburgh), FWA00006735 (University of Pittsburgh Medical Center), FWA00000600 (Children's Hospital of Pittsburgh), FWA00003567 (Magee-Womens Health Corporation), FWA00003338 (University of Pittsburgh Medical Center Cancer Institute).

Please be advised that your research study may be audited periodically by the University of Pittsburgh Research Conduct and Compliance Office.

APPENDIX C: OCCUPATIONAL DISTRIBUTION OF PSYCHOSOCIAL JOB CHARACTERISTICS



*Labels for forty seven occupations could not be printed due to lack of space (computer based label routine).

FIGURE 1—The Occupational Distribution of Psychosocial Job Characteristics
SOURCE: US QES Surveys, 1969, 1972, 1977.
N: 2,897 males

summary measures were computed across the age groups, the estimated odds were 2.48 (chi-square MH = 6.32, p = .012) and 3.28 (chi-square MH = 10.18, p = .001), respectively, for the HES and HANES. Using the overall rate of "high strain" and the estimates of the underlying odds, the estimated attributable risk is .25 and .33, respectively, for the HES and the HANES. While this analysis fails to control for many important factors in myocardial infarction (e.g., race, blood pressure, cholesterol and smoking status), it is striking that controlling for age alone, "job strain" accounts for

APPENDIX D: PAIRWISE T-TESTS BY JOB CLASS AND JOB STRAIN

Table 10. Pairwise T-Tests by Job Class and Job Strain

Variable	Description	Significant Observations (p<0.05), (p<0.1)	
		Job Class	Job Strain
pdcmbb1	Proportion Days Covered (PDC) for beta blockers (BB) medication class post-intervention		• Low Strain (.9156) vs. High Strain (.5731); p=0.0230
pdcmraas0	Proportion Days Covered (PDC) for renin angiotensin system antagonists (RASA) medication class pre-intervention		• Low Strain (.8668) vs. Active (.6435); p=0.0076 • Low Strain (.8668) vs. Passive (.5629); p=0.0020 • Low Strain (.8668) vs. Non-Contributing (.5071); p=0.0003
pdcmstat0	Proportion Days Covered (PDC) for statins medication class pre-intervention		• Active (.6452) vs. High Strain (.4681); p=0.0230 • Low Strain (.6555) vs. High Strain (.4681); p=0.0534
pdc80bb0	Proportion Days Covered >80% (PDC80) for beta blockers (BB) medication class pre-intervention	• Nonmanual (.6512) vs Manual (.3846); p=0.0312	
pdc80ccb0	Proportion Days Covered >80% (PDC80) for calcium channel blockers (CCB) medication class pre-intervention		• Active (.7273) vs. High Strain (.3125); p=0.0102 • Low Strain (.875) vs. High Strain (.3125); p=0.0077
pdc80raas0	Proportion Days Covered >80% (PDC80) for renin angiotensin system antagonists (RASA) medication class pre-intervention		• Low Strain (.75) vs. Non-Contributing (.3); p=0.0168
mdage	Age	• Not Working (65.78) vs. Manual (60.26); p=0.0596 • Not Working (65.78) vs. Nonmanual (59.99); p=0.0354	
mdf	Female	• Nonmanual (.625) vs. Manual (.28); p=0.0000 • Not Working (.7222) vs. Manual (.28); p=0.0008	• High Strain (.8529) vs. Active (.5781); p=0.0054 • Active (.5781) vs. Low Strain (.2727); p=0.0040 • High Strain (.8529) vs. Low Strain (.2727); p=0.0000 • High Strain (.8529) vs. Passive (.4047); p=0.0000 • Non-contributing (.6667) vs. Low Strain (.2727); p=0.0089
mdedm1	Individual has less than a high school degree	• Manual (.3) vs. Nonmanual (.0756); p=0.0001 • Not Working (.4737) vs. Nonmanual (.0756); p=0.0000	• High Strain (.3143) vs. Active (.0476); p=0.0002 • Passive (.2143) vs. Active (.0476); p=0.0082 • Non-Contributing (.5333) vs. Active (.0476); p=0.0000 • High Strain (.3143) vs. Low Strain (.0606); p=0.0073 • Non-Contributing (.5333)

Table 10 continued

Variable	Description	Significant Observations (p<0.05), (p<0.1)	
		Job Class	Job Strain
			vs. Low Strain (.0606); p=0.0001 • Non-Contributing (.5333) vs. Passive (.2143); p=0.0201
mdedm2	Individual has a high school degree	• Manual (.5) vs. Nonmanual (.1849); p=0.0000	• Low Strain (.3636) vs. Active (.1429); p=0.0126 • Passive (.4286) vs. Active (.1429); p=0.0009
mdedm3	Individual has a four-year degree	• Nonmanual (.3529) vs. Manual (.12); p=0.0020	
mdedm4	Individual has a professional/graduate level degree	• Active (.5556) vs. High Strain (.0857); p=0.0000 • Active (.5556) vs. Low Strain (.2424); p=0.0031 • Active (.5556) vs. Passive (.0952); p=0.0000 • Active (.5556) vs. Non-Contributing (0); p=0.0001 • Low Strain (.2424) vs. Non-Contributing (0); p=0.0373	• Nonmanual (.3866) vs. Manual (.08); p=0.0001 • Nonmanual (.3866) vs. Not Working (0); p=0.0008
mdmarpar	Individual is married/partnered	• Nonmanual (.6807) vs. Not Working (.3158); p=0.0020	• Active (.7302) vs. High Strain (.5149); p=0.0316 • Active(.7302) vs. Non-Contributing (.2667); p=0.0006 • Low Strain (.6364) vs. Non-Contributing (.2667); p=0.0170 • Passive (.6191) vs. Non-Contributing (.2667); p=0.0186
mdlivhom	Independent living		• Active (.9683) vs. Passive (.8809); p=0.0803 • Active (.9683) vs. Non-Contributing (.8); p=0.0165
mdemp1	Employed full-time	• Nonmanual (.3949) vs. Manual (.24); p=0.0542 • Manual (.24) vs. Not Working (0); p=0.0185 • Nonmanual (.3949) vs. Not Working (0); p=0.0006	• Active (.4127) vs. High Strain (.1714); p=0.0144 • Active (.4127) vs. Non-Contributing (0); p=0.0020 • Low Strain (.4545) vs. High Strain (.1714); p=0.0111 • Low Strain (.4545) vs. Non-Contributing (0); p=0.0012 • Passive (.2857) vs. Non-Contributing (0); p=0.0195
mdemp3	Retired		• Active (.4444) vs. Passive (.2619); p=0.0587
mdemp4	Disabled	• Manual (.26) vs. Nonmanual (.0840); p=0.0022 • Not working (.4737) vs. Nonmanual (.0840); p=0.0000	• High Strain (.3142)vs. Active (.0476); p=0.0002 • Passive (.1904) vs. Active (.0476); p=0.0190 • Non-Contributing (.5333) vs. Active (.0476); p=0.0000 • High Strain (.3143) vs. Low

Table 10 continued

Variable	Description	Significant Observations (p<0.05), (p<0.1)	
		Job Class	Job Strain
			Strain (.0606); p=0.0073 • Non-Contributing (.5333) vs. Low Strain (.0606); p=0.0001 • Non-Contributing (.5333) vs. Passive (.1905); p=0.0106
mdemp5	Not employed		• High Strain (.1429) vs. Active (.0317); p=0.0411
incc1	Current income between $0 - $15,000	• Not Working (.5333) vs. Nonmanual (.1897); p=0.0027	• High Strain (.3235) vs. Active (.1290); p=0.0221 • Passive (.3095) vs. Active .1290); p=0.0244 • Non-Contributing (.6364) vs. Active (.1290); p=0.0001 • Non-Contributing (.6364) vs. Low Strain (.1333); p=0.0008 • Non-Contributing (.6364) vs. Passive (.3095); p=0.0476
incc2	Current income between $15,001 - $30,000		• High Strain (.3824) vs. Active (.1613); p=0.0150 • Low Strain (.3667) vs. Active (.1613); p=0.0278
incc3	Current income between $30,001 - $50,000	• Nonmanual (.2328) vs. Not Working (0); p=0.0362	
incc4	Current income between $50,001-$75,000		• Active (.2097) vs, Passive (.0476); p=0.0209 • Low Strain (.2) vs. Passive (.0476); p=0.0431
incc5	Current income between $75,001-$100,000	• Nonmanual (.1034) vs. Manual (0); p=0.0206	• Active (.1290) vs. High Strain (0); p=0.0288
incc6	Prior income is more than $100,000		• Active (.0451) vs. High Strain (0); p=0.0194 • Active (.0451) vs. Low Strain (0); p=0.0281
incp1	Prior income is between $0 - $15,000	• Not Working (.5) vs. Nonmanual (.1667); p=0.0136	• Non-Contributing (.4285) vs. Active (.1190); p=0.0410
incp2	Prior income is between $15,001 - $30,000		• High Strain (.3214) vs. Active (.0714); p=0.0061 • Non-Contributing (.4286) vs. Active (.0714); p=0.0069
incp5	Prior income is between $75,001 - $100,000		• Active (.1429) vs. Passive (0); p=0.0584
incp6	Prior income is more than $100,000		• High Strain (.0357) vs. Active (.3095); p=0.0045 • Active (.3095) vs. Low Strain (.05); p=0.0222 • Active (.3095) vs. Passive (0); p=0.0024
mdbins5	Insured via Medicare		• Passive (.1190) vs. Active (.0156); p=0.0242 • Non-Contributing (.1333)

Table 10 continued

Variable	Description	Significant Observations (p<0.05), (p<0.1)	
		Job Class	Job Strain
			vs. Active (.0156); p=0.0320
mddrqs1	When you visit your doctor, how often do you prepare a list of questions for your doctor?	• Nonmanual (3.35) vs. Manual (2.8); p=0.0439 • Not Working (3.833) vs. Manual (2.8); p=0.0224	• Passive (3.524) vs. High Strain (2.794); p=0.0474
mddrqs2	When you visit your doctor, how often do you ask questions about the things you don't understand about your treatment?	• Nonmanual (4.492) vs. Manual (3.88); p=0.0256	
mddrqs3	When you visit your doctor, how often do you discuss any personal problems that may be related to your illness?		• High Strain (3.882) vs. Low Strain (3); p=0.0443
mdhealth	In general, you would say your health is?	• Manual (3.36) vs. Nonmanual (2.95); p=0.0078	• Passive (3.309) vs. Low Strain (2.939); p=0.0508

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